Understanding The Impact Of Online Platforms On Human Society And Relationships: A Macro And Micro Perspective

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Dedication

To my Parents,

Amrita Mojumder

and

Late Partha Sarathi Mojumder

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Overview

Online intermediaries along with their IT-enabled features have ushered a new era for the human society. It has affected all aspects of life from cultivating intimate relationships to unintentionally causing societal challenges. Particularly, online platforms allow users to engage in online market places, where certain platforms allow men and women to connect with each other to pursue inter personal exchanges. For example, online dating platforms allow singles looking for mates, find partners who agree to go for dates, where consensual intimate sexual experiences, like hook ups, can be a consequential outcome. In another situation, in online classified advertisement platforms, sex workers can illegally post ads to solicitate clients. The characteristics of online platforms along with their IT-enabled features have influenced this process. This dissertation examines two questions looking at such interactions in a causal manner. First, it studies the impact of entry of an online classified advertisement platform, Craigslist, on prostitution trends, which is an unintentional consequence of website operation. Second, the dissertation looks at the impact of an important IT-enabled feature, the *vote-identity revelation* feature, on user engagement and matching outcomes in dating websites.

In literature concerning sexuality and economics, we find that sexual interactions between men and women can be looked at using an economic approach (Baumeister and Vohs 2004). From the seminal research stream based on Nobel laureate Gary Becker's (1976) framework, we know that human behavior follows four main assumptions. First, under a market system, individual behavior is shaped by individual choices that consider costs and benefits of situations. Second, market influences the allocation of scarce but coveted resources. Third, the rule of competition guides seller's behavior. Finally, individuals seek to maximize their outcomes. Using this economic framework, Baumeister and Vohs (2004) modeled negotiations concerning sexual activities as economic decisions, where men and women are participants in the role of buyers and sellers in a marketplace. This model encapsulates prostitution as a bare-bone type of sexual exchange, whereby clients give sex workers money in return of sexual favors. It also explains dating and courtship as a process where eventually men use persuasion to engage in sexual activities with their female partners. From an economic point of view, men invest in time and resources towards their female partners, like buying them gifts, in order to negotiate sexual favors (Baumeister and Vohs 2004). This dissertation builds upon the economic approach on human sexuality as mentioned in Baumeister and Vohs (2004), and looks at the market of dating and prostitution in online exchange scenarios.

The internet and its online platforms with IT-enabled features can provide design elements to facilitate an online marketplace. These online market "clearing houses" can facilitate the activities of finding a partner for intimate relationships. Accordingly, the dissertation relates to the extant literature on online intermediaries. The IT-enabled features available inside online intermediaries can impact the payoffs and cost dynamics faced by men and women on both sides of the market. Extant literature on platform economics posits that online intermediaries bring about reduced search costs (Bakos 1997, Hann and Terwiesch 2003), facilitate online communication across spatial and temporal boundaries (Bailey and Bakos 1997), and provide a broader base of product offerings (Brynjolfsson et al. 2003). For these set of reasons, online intermediaries can make it easy for men to find sex workers or find strangers to date. First, platforms allow their users to experience various cost reductions of participating in dating and prostitution markets. Second, men and women can use online communication features to better gauge their interpersonal affordances and strike an efficient deal. Past research in e-commerce has found that well-designed websites are able to facilitate greater purchase intentions (Hausman and Siekpe 2009). Online features such as product presentation formats (Jiang and Benbasat 2007), product comparison tools (Häubl and Trifts 2000), and online product reviews (Zhu and Zhang 2010) that are incorporated in online sites can boost online purchase significantly. Similarly, when making decision on an intimate partner, users can access key information about their potential partner through online site features and make an informed and safe decision. Whether a john negotiates a price with a sex worker, or a young man asks his likable other out for a date, the online websites can provide design features to facilitate each process. Third, as an online aggregator, online platforms offer a broader variety of products and services compared to the physical stores. Online platforms facilitate the long tail phenomenon (Brynjolfsson et al. 2011), by which consumers with specialized preferences can discover and locate niche products through online search tools. For example, johns and single men searching online for a sex worker or a date, are not limited to a specific ethnicity. Nonconventional preferences could be met with websites catering niche user groups. Accordingly, the dissertation explores the role of online intermediaries at facilitating the diverse yet similar markets of prostitution and dating.

In my first essay, I tackle a macroscopic view on how internet is transforming the sex trade. Extant literature has portrayed that internet acts as a hub for sex work by providing an intermediation role (Perer 2012). Accordingly, it facilitates information exchange between buyers and sellers of sexual services. One such online platform engaged in facilitating the market for sex work was Craigslist, the earliest and largest online classified website for this market. Utilizing Craigslist's expansion in the United States as a natural experiment my first essay tries to quantify the economic impact due to Craigslist's entry on prostitution trends. Further, it examines the potential pathways in which the Craigslist website could affect the market for sex workers.

To study the potential pathways, we look at independent sex workers and sex workers who are operating under organized crime agencies. It is of interest to identify which cohort of sex workers are gaining from posting sexual services advertisements in Craigslist's portal. Further, we check whether Craigslist's entry caused uptake in prostitution in markets with no history of sex work or that having a culture of prostitution. In a similar sense, we look for impact of Craigslist's entry along geographic spillovers of sex work, encouragement of sexual types in offer, market for new entrants, domain for police sting operations, and last but not the least, how Craigslist advertisement channels impact sex work. The study uses a difference-in-difference regression of prostitution counts on Craigslist's entry. Our regressions use county and year fixed effects on a panel data set consisting of 1796 counties from 1999 to 2008. Further, the analysis includes covariates to control for demographic characteristics, socio-economic factors, and crime related factors. In sum, our approach aims to derive a causal view of the proposed relationship.

In the second essay, using a microscopic view we look at how IT enabled technologies impact human relationships in an online dating market. Specifically, we study the impact of a popular IT-enabled feature called the *vote-identity revelation* feature on online dating users' engagement and matching outcomes. In this study we use a randomized field experiment on users of one of the largest online dating websites in United States, where the intervention reveals voter's identity-descriptive information. The study looks for both main treatment effects and more importantly heterogeneity in treatment effects along the following dimensions – gender, age groups, ethnicity, and body type.

We are further interested to look for heterogeneity in impact of the *vote-identity revelation* feature along user's attractiveness dimension. Extant literature on attractiveness finds that attractive people do better than unattractive people (Eagly et al. 1991). As a consequence, attractive individuals can become selective given that they have access to more alternatives. Accordingly, the essay looks at the impact of the treatment when interacted with user's own attractiveness, user's average voters' attractiveness, and both. With regards to the effect of user's own attractiveness, we expect to see an "ego effect" where users can become selective in their online dating activities. When considering user's average voters' attractiveness, we expect to see an "encouragement effect" due to votes from highly attractive voters.

The thesis makes contribution to show the dichotomy in use of IT-enabled technologies which can facilitate both legal and illegal markets. On one hand, websites dedicated to online dating have improved substantially the experience of finding the right date for users. On the other hand, perhaps, in an unintended manner, online classified advertisement platforms have led to societal challenges due to spread of illegal prostitution activities. The fine line between a legal activity and an illegal activity is traversed quite easily due to differential IT-enabled marketplace designs constituting online platforms. Therefore, the agencies involved in creating and monitoring online platforms should be responsible towards maintaining scrutiny for technologies proper societal use. Yet, legal affordances like the section 230 of the communication decency act (Ehrlich 2002) shield websites from liability for unlawful advertisement postings made by third parties. Consequently, websites like Craigslist and Backpage have become a haven for prostitution-related ads.[1]

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[1] Recently, newly launched federal policies like Stop Enabling Sex Trafficking Act (SESTA) and Fight Online Sex Trafficking Act (FOSTA) are amending section 230 in order to take down online websites that facilitate illegal markets, like that of sex trafficking. As a result, legal agencies are also actively working towards facilitating technologies proper societal use.

Next, we look deeper into the market of online prostitution. In this market, the clients pay a monetary price for sexual services. Cunningham and Kendall (2011) found that online sex workers have characteristics unlike those of traditional sex worker stereotypes, for instance, a high proportion of online sex workers have college education and hold health insurance, which suggests online sex workers are likely to work independently. Further research also found that organized crime rings are using the Internet to facilitate prostitution (McAllister 2011, Finn and Stalans 2016). This suggests that both independent sex workers and those coerced by organized vice agencies operate in online markets. To fight with online prostitution, law enforcement conducts online sting operations. Accordingly, the market participants in online prostitution markets need to employ discreet and anonymous market clearing setups to avoid arrests, and they need to find ways to look out for their own safety before agreeing to take part in a sexual service exchange. When considering an online classified platform like Craigslist, its unassuming lean website design and discreet IT-features helps maintain anonymity for its users in the marketplace. In this backdrop of simplistic IT interface design, sex workers can post short unassuming ads, which can make Craigslist unintentionally become the haven for sex work. In addition, Craigslist primarily operate as clearing houses for regular use products and services. This provides enhanced network effects for the website from being a well-known classified advertisement portal, and can bring awareness of an online prostitution market if such a market is operational on the website.

Next, we look at the online dating markets, where individuals can search and access a vast number of potential mates online who were out of reach in earlier times. The online dating websites can facilitate spatial and temporal communication, whereby men and women can view each other's online profiles and send private messages of intent. Further online dating website's recommendation and matching algorithms can sift through thousands, or even millions of user profiles, and try to provide matches between dating partners. These sophisticated recommendation and matching algorithms take into consideration the large number of interpersonal and preferential requirements that users inform regarding their personal relationship choices. Therefore, these online dating websites are driven to provide a *superior* relationship than dating offline in order to have a business value (Finkel et al., 2012). For instance, PlentyOfFish claims that its members send "1 billion messages a month," and OkCupid claims "We use math to find you dates[2]" (PlentyOfFish.com 2017, OkCupid.com, 2017). These examples establish the competitive nature of online dating marketplace where websites are in a constant struggle to provide new and useful value to their customer base. Accordingly, these websites are continuously toying with a plethora of high-end IT-enabled features, and are continuously trying to discover the right mix of features that can make the task of finding a date easier, efficient, and superior. In order to do so, online dating websites typically operate using a *freemium* business model, where at the beginning of the membership all users sign up for

[2] OkCupid also claims in their website "We work our algorithm magic to find people you'll actually like." (OkCupid.com, 2017)

a free account that allows users to access a basic set of IT-enabled features. Users can obtain a premium subscription that comes with a fixed bundle of high-end IT-enabled features. These high-end features claim to substantially improve the users experience towards achieving their dating related goals. Therefore, identifying highly effective IT-enabled features will add value to both online dating firms and their user base. Therefore, in the second essay of this thesis, we look using a microscopic view at the impact of an important IT-enabled feature known as the *vote-identity revelation* feature. Accordingly, this study contributes to identify the value of an important IT-enabled feature in a two-sided market, where increase in user engagement and matching are of critical value, given the competitive scope of the online dating marketplace.

Essay 1 - The Digital Sin City: An Empirical Study of Craigslist's Impact on Prostitution Trends

1. Introduction

In recent years, the Internet is transforming the sex trade. Perer (2012) portrays the Internet as a "virtual red-light district" which plays the intermediary role of facilitating information flow between sex workers and buyers, making it easier for these individuals to strike mutually satisfactory deals, and engage in paid sexual transactions. Even in the United States where prostitution and its facilitation are illegal everywhere except Nevada, the marketing and arrangement of commercial sex is moving online. In particular, online classified advertising sites and underground "entertainment" sites have become the go-to avenues to advertise and set up transactions for paid sexual services. Despite the illegality of selling sexual services online, the dated Section 230 of Communications Decency Act (CDA) shields websites from liability for unlawful postings made by third parties.[3] Consequently, the websites like Craigslist have become a haven for prostitution-related ads.[4]

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[3] Further details on Section 230 of the CDA are available at Ehrlich (2002).

[4] A Craigslist blog post revealed that there are at least 700,000 prostitution ads posted on the site within a year. See http://blog.craigslist.org/2010/08/18/ manual-screening-matters/, accessed on June 17, 2015.

Craigslist is one of the largest online classified service website that offers a dedicated section for prostitution ads in the 2000s. Advertisements for sexual services were posted under the section “Erotic Services,” which was subsequently renamed as “Adults Section” in 2009 after numerous complaints were made against Craigslist. The website faces intense public scrutiny over the years, as many believed that the website’s operators have knowingly allowed ads that offer paid sexual services to be posted on the site. The continuous pressure from a group of state attorneys general finally led to the closure of the Adults Section in September 2010. Despite the illegality of selling sexual services online, Section 230 of Communication Decency Act (CDA) shields websites, such as Craigslist from liability for unlawful postings by third parties, which allowed the platform to serve prostitution ads for close to a decade. This brings up a natural question on whether amendments should be added in the current CDA such that the 20-year old policy does not bear unintended consequences of fostering illegal activities online. Although there are anecdotal accounts that link Craigslist to prostitution acts, no studies known to date has systematically and formally examined the relationship between the site entry and prostitution.

Past work has examined the textual aspects of the online solicitation ads and conducted interview studies with a few selected sex workers, without assessing the overall impact that online solicitation sites have on actual prostitution incidence (Castle and Lee 2008, Hemmingson 2008). The lack of research on the impact of solicitation sites on prostitution trends is surprising, given that prostitution constitutes as an illegal market that has far reaching social consequences. While a portion of sex workers might be made up of willing individuals who needed an income source, the paid sex industry is also facilitated by organized vice groups (Cho et al. 2013). Worth $32 billion annually, the global sex trade is one of the fastest growing forms of commerce today (Deshpande and Nour 2013). Motivated by the lucrative source of monetary profits that prostitution provides, organized vice groups engage in sex trafficking to supply the trade with sex workers from both developed and under-developed countries (Schauer and Wheaton 2006, Hanna 2002). Moreover, prostitution is often accompanied by other types of crimes, such as drug abuse and drug trade (Hanna 2002). With the introduction of online platforms, organized crime groups have begun to make use of this new channel to further expand their operations. In light of this pressing issue, this study aims to shed light on this phenomenon by investigating the role of online intermediaries and quantify its economic impact on prostitution incidence.

Using a national panel data set, we examine the longitudinal relationship between Craigslist's entry and prostitution trends in 1,796 U.S. counties from 1999 to 2008. To empirically identify the entry effects on prostitution incidence, we rely on a natural experiment setup inherent in Craigslist's expansion pattern in the United States. During its expansion, Craigslist was launched in different locations in a staggered fashion across the years. Thus, in a given year, there is a subset of counties with Craigslist and another set of counties that do not. Given that each Craigslist site is location-specific, the prostitution ads posted on the site would cater specifically to the population living within the location. This unique entry setting allows for the quantitative comparison of 'treated' counties with 'control' counties. Exploiting the natural experiment framework, we run difference-in-difference panel regressions of prostitution incidence on Craigslist's entry with county and year fixed effects, and include controls to account for demographic, socioeconomic, and crime-related factors that may affect prostitution trends. We further perform a series of robustness checks including the use of counties with active prostitution cases in our estimation, alternative dependent variables and model specifications, various matching schemes to identify comparable treatment and control counties, and performing falsification checks to check for spurious results. Additionally, we repeat our analyses at the Metropolitan Statistical Area (MSA) level and utilize population-normalized prostitution counts to assess the robustness of the results.

Our empirical analysis reveals that the entry of Craigslist holds a positive relationship with prostitution trends. Site entry is found to result in a 17.58 percentage increase in prostitution cases. We find that sign and significance of our main results are robust under alternative variable definitions and model specifications. Falsification tests indicate that the relationship between site entry and prostitution cases is unlikely to arise spuriously, and that a pre-entry trend leading to an increase in prostitution trends was absent. We uncover several underlying mechanisms related to the main phenomenon:

1. The prostitution market facilitated by Craigslist is made up of both independent sex workers and workers operating under commercial vice groups, though the latter constitute a larger market share.

2. Craigslist’s entry increases prostitution in both counties that have existing prostitution trends and those that do not, though the former set of counties experience a larger growth relative to the latter.
3. The entry of Craigslist generates spillover effects to neighboring counties without Craigslist.
4. There is an increase in online sex workers who provided exotic sexual services. However, this increase is relatively small compared to workers who provided the traditional escort services.
5. Craigslist increases prostitution by inducing more solicitation from existing workers, and also by attracting more entrants to the market.
6. The increase in prostitution arrests happens at a slower rate compared to the increase in prostitution.
7. A complementary effect between erotic and casual sex ads on prostitution trends exists.

Our paper aims to make a few key contributions. First, our study contributes broadly to the emerging literature on the societal challenges associated with online intermediaries and Internet penetration (Burtch and Chan 2017, Chan and Ghose 2014, Chan et al. 2016, Greenwood and Agarwal 2015). Although the use of the Internet holds both positive and negative impacts towards the society, extant work has largely focused on examining the former while overlooking the downsides of the Internet. Responding to the call for research on the societal challenges and drawbacks of digital technologies

(Fichman et al. 2015, Majchrzak et al. 2012), our investigation of Craigslist's impact on prostitution trends seeks to bring about greater awareness and understanding of the vulnerabilities introduced by online technologies, so that proper technological design and policy changes can be introduced. While Chan and Ghose (2014) have focused on the detrimental impact of online intermediaries on public health, our study has taken the route of uncovering the impact of such platforms on prostitution incidence, which constitutes as another important social issue. In this sense, our work contributes additionally to this literature by providing a broader understanding of the criminal impacts of online technologies.

Second, our findings also add to the literature of platform economics (Rochet and Tirole 2003). Extant literature has largely examined the transactional impacts of online platforms for markets with lawful normal goods, with few or no studies investigating its impact on illegal goods. Given that the high costs of providing and consuming illicit services via legal punishment, online prostitution represents a different class of goods that bear unique nuances that warrant further examination in relation to platform economics. Our study results attempts to enrich this literature by providing first-hand empirical evidence towards the phenomenon and uncovering underlying pathways for the relationship, helping to pave inroads towards a deeper theoretical understanding of illicit markets function under online intermediation.

Third, by shedding light on the various underlying mechanisms that govern the growth in prostitution trends facilitated by Craigslist's entry, our study makes the practical contribution of providing actionable, policy-relevant insights needed for the effective implementation of strategies and interventions for curbing the proliferation of the underground sex trade, with a particular focus of facilitating deeper discussions on Section 230 of the CDA. Moreover, the understanding of the various mechanisms of the platform-enabled prostitution serves to expose ‘how’, ‘why’, and ‘where’ the sex trade would flourish in the Internet era, allowing for a more efficient allocation of law enforcement resources.

2. Study Context and Related Literature

2.1. Craigslist

Craigslist started in early 1995, and is the leading online classified service provider in the United States in the 2000s. With the launch of the “Erotic Services” section in 2001, Craigslist website served as a portal for prostitution advertisements (Farley et al. 2013). By 2005, Craigslist had become a virtual prostitution hub, hosting 25,000 new prostitution-related ads every ten days in the United States (Farley 2006). A typical prostitution ad can either explicitly indicate the provision of sexual services or implicitly suggest similar services via sensual massage services. These solicitation ads tend to include provocative photographs and provide information such as hourly rates, phone numbers, descriptions of worker’s body measurements, and keywords like “busty”, or “fantasy girl” (Sandoval 2009). In March 2009, Craigslist was sued for facilitating prostitution and that it was a public nuisance (Dart vs. Craigslist, 2009). In response, Craigslist made token changes to the site by announcing that minors should not use its erotic services section, providing links to anti-trafficking websites, and started to charge $10 to users who post in the "Adult Service" section (Sarno 2009). Following more complaints on Craigslist, seventeen state attorneys general requested the immediate removal of the adult services section in August 2010. A month after the request, Craigslist voluntarily shut down its adult services section (Lindenberger 2010).

Despite actions taken to suppress the posting of prostitution ads on Craigslist, prostitution ads started to appear in other sections of the site (e.g., personals section) (Louie 2010). Furthermore, following Craigslist's closure of the adult services section, other online platforms (e.g., Backpage.com and MyRedBook) assumed the role of facilitating online solicitation (Chansanchai 2011). Most of these alternative solicitation sites remain active and are not shut down, indicating that the selling of sexual services on classified ad sites persist beyond the closure of Craigslist's adult section. Thus, it remains imperative to understand the link between site entry and prostitution, as study findings provide insights that would be useful for curbing prostitution trends facilitated by other similar online intermediaries.[5]

The study of Craigslist's impact on the prostitution market is also valuable in that it sheds light on online platforms in context of illicit goods, a topic that is not well understood. Since the early days of ecommerce, most of the IS literature has focused on

[5] We chose Craigslist as the site of study as its entry patterns are likely to be exogenous which helps to facilitate a cleaner empirical identification as compared to other sites (e.g., Backpage.com). More details are provided in the subsequent sections.

examining the influence of digital platforms in the context of legal goods. For instance, the seminal digital platform paper by Bailey and Bakos (1997) discusses the emerging roles of online intermediaries in the retail and automotive industry. Similarly, other works have looked at the influence of online platforms on normal goods, such as books and newspapers (Brynjolfsson et al. 2003, Seamans and Zhu 2013). Even recent IS papers that examine newer forms of two-sided platforms (e.g., online dating, crowdfunding, online labor markets) shied from examining illegal goods (e.g., Bapna et al. 2016, Burtch and Chan 2017, Chan and Wang 2017).[6] Given that illegal markets bear key differences from legal markets, studies rooted in legal goods may not fully illuminate the effect of online platforms on the nuanced characteristics of illegal goods. A noteworthy difference pertains to the additional costs that market participants for illegal goods face (i.e., imprisonment, fines, and evasion costs) which are otherwise not present in the market for legal goods (Becker 1974, Bouchard and Wilkins 2013). Moreover, the illicit act of buying and selling these goods imply that market participants would not have a formal recourse when faced with non-satisfactory transactions (i.e., non-payment, low quality services). We discuss the focal study relationship in light of these aspects next.

[6] We note that Chan and Ghose (2014) and Cunningham et al. (2017) have looked at negative social impacts of Craigslist (i.e., HIV incidence, violence against women). However, these are not in the context of goods/services.

2.2 Rational Choice Theory and Online Prostitution

Based on Becker's (1974) framework on the economics of crime, the decision to engage in a criminal act is a rational process in which individuals make choices that maximizes their utility. Accordingly, under the rational choice theory, an individual chooses to commit a crime if the total payoffs of the illicit act are higher than its associated costs of legal punishment. Similarly, in making a choice to participate in the prostitution market, the providers and clients alike would weigh the relative benefits and costs when deciding whether to engage in paid sexual transactions. From the perspective of the supply-side, the main benefits of participating in this market lie largely in the financial gains.[7] From the perspective of the demand-side, the incentive to participate in the market is mainly for the satiation of sexual desires. Common to providers and clients, the costs of market participation involve legal punishment that comes in the form of fines and imprisonment.[8] Under the shield of the Section 230 of the CDA, site owners do not bear

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[7] We understand that this can be an over-simplification of the situation faced by service providers, as sex workers may not have aligned interests with the agency or the pimps, especially in the case of involuntary prostitution. However, this distinction is not crucial in this study as we are examining the aggregate prostitution levels induced by the entry of Craigslist, which is ultimately driven by financial motives.

[8] Generally speaking, the structure of the laws is set up to punish the leaders and facilitators of organized prostitution more severely than the sex workers and the clients,

any cost for facilitating prostitution, as they are not held responsible for the interactions between users.

With the introduction of an online intermediary, the payoffs and costs faced by participants in the prostitution market are subjected to changes that can influence the existing prevalence of prostitution. Extant literature on platform economics posits that online intermediaries bring about reduced search costs (Bakos 1997, Hann and Terwiesch 2003), facilitate online communication across spatial and temporal boundaries (Bailey and Bakos 1997), and provide a broader base of product offerings (Brynjolfsson et al. 2003). Similarly, the entry of the Craigslist platform into specific locations is likely to increase local incidence of prostitution for the same set of reasons. First, the Craigslist platform allows its users to experience various cost reductions of participating in the prostitution market. Sex workers soliciting through the platform have lower search costs as they need not to 'walk the streets' to solicit customers, and clients need not travel to red-light districts to search for sexual services. In addition to eliminating search costs, a reduction in cost also comes in the form of reduced probability of arrests and detection as the sex workers and clients soliciting on Craigslist can work out transactional details using online messages and emails (Cunningham and Kendall 2011), thereby reducing physical exposure to policing agencies during the solicitation process. Compared to seeking prostitutes in red light districts, brothels, or massage parlors, the online search for

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through longer jail terms. For more details, please refer to http://prostitution.procon.org/view.resource.php?resourceID=000119.

prostitutes also preserves the anonymity and privacy of clients (Grewal et al. 2004), lowering the perceived risk of legal punishment and detection. Further, given that the posting of solicitation ads on Craigslist is free, sex workers would avoid advertising cost,[9] which is otherwise present when posting ads in traditional medium (e.g., classified ads in newspapers).

Second, sex workers and clients communicating on the online platform can better plan sexual transactions with the affordance of Internet technologies. Past research in ecommerce has found that well-designed websites are able to facilitate greater purchase intentions (Hausman and Siekpe 2009). Online features such as product presentation formats (Jiang and Benbasat 2007), product comparison tools (Häubl and Trifts 2000), and online product reviews (Zhu and Zhang 2010) that are incorporated in online sites can boost online purchase significantly. Similarly in the sales of sexual services, online technologies can enhance transaction volume by allowing clients to better assess key attributes of sex workers as they are making purchase decisions. For instance, through the photos posted on Craigslist ads and emails, clients are able to perceive not only the facial attractiveness of workers (e.g. a profile headshot) but also sensitive bodily attributes via nude photos, which is otherwise difficult to assess in when soliciting in a public space. At the same time, clients are able to compare service attributes across workers listed on Craigslist with greater ease, as the transaction information (e.g., price, service duration,

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[9] Craigslist only started charging a posting fee for escort ads in 2009. The site has allowed the free posting of such ads since the launch of this section in 2001.

types of sexual service provided, travel requirements such as in-calls or out-calls) are readily available within the ads or email communications (Häubl and Trifts 2000). Furthermore, through specialized online review sites (e.g., TheEroticReview.com, NaughtyReviews.com, PunterNet.com), clients can cross-check on the service quality of the listed workers based on the experiences of other clients (Hughes 2004). Additionally, online providers can screen out risky clients before physically meeting them by searching client's name or telephone number from public databases to check if they have past records of violence or criminal involvement (Brooks 2009). Thus, the availability of these online affordances creates a more efficient matching process, and can heighten the prostitution transactions in locations served by Craigslist.

Third, as an online aggregator, online platforms offer a broader variety of products and services compared to the physical stores. Online platforms facilitate the *long tail* phenomenon (Brynjolfsson et al. 2011), by which consumers with specialized preferences can discover and locate niche products through online search tools. Compared to the traditional prostitution market in which the ethnicity of the sex worker is highly dependent on the physical location in where the service is offered (Dank et al. 2014),[10] the workers operating on the Craigslist platform are not limited to a specific ethnicity. Further, a consistent motive for why clients seek prostitution services is to engage in a different kind of sex that they cannot receive from non-prostitutes, such as

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[10] For instance, Latina brothels usually house Hispanic sex workers, while massage parlors primarily house Asian sex workers.

dominance and submission, role playing, and various sexual fetishes (Månsson 2006, Monto 2004). Clients could locate these nonconventional services more easily, as online platforms host a variety of sex workers by which a broad assortment of paid sexual services may be solicited, including niche sexual services. Consequently, this facilitates more matches in the market of paid sexual services that is characterized by highly heterogeneous preferences.

2.3 Related Literature on Online Prostitution

While extant work reports that a majority of street prostitutes are associated with organized prostitution rings (Farley et al. 2013, Helfgott 2008), the current literature does not provide a clear view of the operating structure of online prostitution enabled by platforms. On the one hand, it is plausible that a majority of the solicitation ads are posted by willing participants who are not part of organized vice groups, in the attempt to capitalize on the financial gains of providing sexual services in this market. Cunningham and Kendall (2010) found that online sex workers have characteristics unlike those of traditional sex worker stereotypes, for instance, a high proportion having college education and holding health insurance. Such worker demography suggests that online workers are likely to work independently without pimps and are not coerced into the industry by organized prostitution rings. On the other hand, McAllister (2011) noted that organized prostitution rings are using the Internet to solicit customers. A recent study finds that pimps continued to use platforms such as Craigslist to advertise prostitution services, despite knowledge that these sites are monitored by enforcement agents (Finn and Stalans 2016). A likely reason for this trend is that extensive profits can be reaped from online solicitation (Dank et al. 2014).[11] Given that the lucrativeness of online prostitution, organized prostitution rings are motivated to have a foot in its operations.

Another related issue concerns the geographical growth patterns of online prostitution facilitated by online platforms. There is significant academic interest in examining whether electronic channels affect the consumption patterns and outcomes across locations. For instance, Overby and Forman (2015) find that the presence of an online platform reduces frictions in geographically distributed car markets through increased price visibility and reduced transaction costs, resulting in an increased willingness to travel to further locations to transact. Yet, Lin and Viswanathan (2016) document a home bias in the crowdfunding context, with investors favoring home state borrowers over external borrowers. The equivocality in past findings suggests that the context of interest is likely to have crucial bearings on geographic-related outcomes.

Due to heterogeneous preferences, clients often value having a variety of prostitutes to choose from. Thus, Cunningham and Kendall (2011) reasoned that sex workers are incentivized to congregate spatially where clients can find them, and clients are also incentivized to travel to places where prostitutes are located. With limited enforcement resources, sex workers and pimps would face a lower probability of arrest in locations that have a higher concentration of other prostitutes (Freeman et al. 1996).

[11] Pimps and traffickers interviewed in the study took home \$5,000 and \$32,833 in a week.

These arguments jointly suggest that the growth of online prostitution induced by Craigslist would be larger in locations with existing prostitution trends, compared to locations without existing prostitution activity. Moreover, the impact of Craigslist may also indirectly affect prostitution trends in neighboring locations that are not served by Craigslist. Pimps and sex workers tend to travel to other locations to seek additional business (Scambler 2007), and would likely respond to close-by client requests, leading to spillover effects in these neighboring areas.

Users could solicit sexual acts through different ad sections on Craigslist. On top of the “Erotic service” ads listings, users can also search under the “Personals ads” section to look for non-paid casual hookups among other sex-seeking users. Broadly speaking, the “Erotic service” ads and “Personals ads” can be deemed as facilitating market and nonmarket sexual transactions, respectively (Chan and Ghose 2014). While both market and nonmarket transactions fulfill sexual desires, the motivations to engage in paid sex and casual hookups may not always overlap. Strokoff et al. (2014) find that individuals hookup because they anticipate that a potential relationship to emerge from their encounter. Prevailing social norms indicated by the prevalence of peers with hookup experience can also lead to desires for hooking up (Fielder and Carey 2009). On the other hand, the motives of clients who opt to pay for sex include satisfying the dirty whore fantasy, wanting a different kind of sex from what they can receive from non-prostitutes, and seeking a subservient woman for domination (Milrod and Monto 2012). Given dissimilar motives for seeking each sexual act, these ad sections are likely to serve different needs on top of satiating sexual urges. Recently, qualitative studies have reported instances where the clients are emphasizing deeper and more emotionally rewarding relationships with providers, a phenomenon termed as "The Girlfriend Experience" (Milrod and Monto 2012). Thus, the use of "Personals" and "Erotic service" ads may have a positive, complimentary effect on prostitution trends.

3. Data

To investigate the impact of Craigslist on prostitution, we constructed a nationwide panel data that consists of Craigslist entry patterns and prostitution incidence at the county-year level between 1999 and 2008. In constructing this panel data, we rely on four main data sources, namely TheEroticReview.com (TER), FBI's National Incident-Based Reporting System (NIBRS) database, Craigslist website, and the Census Bureau.[12] Our main dependent variable is $Prostitution_{iy}$, which is a measure of the number of indoor prostitutes in county i for year y. We proxy for prostitution incidence using the count of sex workers with user reviews on TER. Launched in 1998, TER is one of the largest female escort review site, receiving between 500,000 and 1,000,000 unique visitors monthly (Richtel, 2008). The process for submitting a review on TER is highly detailed

[12] As of July 2009, United States has 3,143 counties or county equivalents (http://censtats.census.gov/usa/usainfo.shtml). To avoid issues from selective reporting, counties with sparse observations (i.e., more than one year of missing data) are dropped from the analysis. Main results are largely similar when these observations are included. Table A1 reports the states and counties per state in our data set.

and it requires contributing users to provide several pieces of information about the worker (e.g., physical attributes, prices, service provided, and worker rating).[13] Reviews submitted to the site only become available after several days, as all reviews are routinely checked by TER staff.[14] Using a web scraping script, we collected data on 64,270 escort profiles that had at least one review on TER between 1999 and 2008. Figure A1 reports the distribution of escort profiles based on review counts.

The core advantage for utilizing TER review data as a proxy of prostitution count is that user reviews mirror actual experiences that clients have with sex workers, allowing us to capture sex workers who are active in online solicitation. Issues of fraudulent reviews are less of a concern in our context for two reasons. First, as mentioned earlier, the review data was thoroughly vetted by the staff to ensure that every entry of new

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[13] In submitting a review, TER mandates its users to list the internet contact of the prostitute, for instance, an advertisement on a public classified ads site like Craigslist, a personal website, email (if available), and a telephone number. In addition, reviewers are asked to provide a detailed free-form narrative of their meeting with their encounter with the provider.

[14] Not only do the staff verify that the provided details correspond to the information from the online ads and sites, they also match new incoming reviews with existing workers with reviews by telephone number, website URL, and email address, to minimize duplicate entries for the same worker. The fact that many workers have multiple reviews, indicates that this matching process appears to work reasonably well.

workers are traceable to an online contact, reducing the possibility that a reviewed escort is made up. Moreover, there is no motivation to generate reviews for an escort that does not exist. Second, falsified escort information or reviews do not jeopardize the integrity of the outcome variable, as the main goal of the outcome measure is to capture the count of prostitutes operating in each location and not the quality of these workers. On the contrary, the motives to generate fake reviews (i.e., to enhance business opportunities) are actually helpful in revealing prostitutes who are active in soliciting clients. Regardless, our measure of online reviews falls short in capturing prostitutes who solicited via Craigslist but were not mentioned in the reviews, as a result of clients who have low willingness to write online reviews of their sexual experiences. Because our dependent variable misses out on capturing sex workers that are linked with Craigslist entry but are not reviewed on TER, the estimated entry effect in our regression analyses would likely be an underestimate of the actual entry effect.

In using the TER data, we further refine the coding of our dependent variable by considering four different definitions. Our first measure, *TER: All Years*, simply assumes that the escorts remain active for all years beginning from the year she receives her first review. In our second measure, we factor for the possibility that prostitutes may exit the industry after some time. Accordingly, we consider a sex worker to be active for the years that fall between her first and last review in our second measure, *TER: Active*

Years.[15] Further, given that it is possible that not every escort on TER solicits via Craigslist, we further derive subsets of escorts for the two measures above for prostitutes who have clients who solicited their services via Craigslist. We identify such workers by searching for escorts who have the terms ‘Craigslist,’ ‘CL,’ or ‘Craigs’ mentioned in their reviews. We also consider the measure of number of TER reviews, which proxies for the number of solicitation transactions to supplement to our prostitution count measure, since each sex worker can engage in multiple acts of prostitution.[16]

As an alternative measure of prostitution incidence, we look towards offline policing data from the NIBRS, with which we tabulate the number of arrests made on indoor female prostitutes. The NIBRS data is available under FBI’s *Uniform Crime Report* (UCR) program, a nationwide, cooperative statistical effort that involves close to 18,000 city, university and college, county, state, tribal, and federal law enforcement agencies in reporting crime-related information. Given the consistency in crime reporting standards established over the years across enforcement agencies, crimes reported in the NIBRS are of high levels of accuracy and reliability. Further, the NIBRS reports specific details regarding the crime, including the location in which arrest was made. We rely on

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[15] For a sex worker with only one review, she is coded to be active for that particular year only.

[16] That said, we note that the number of reviews can only serve as proxy for the incidence of prostitution activity since not every service encounter will result in a posted review on TER.

the arrest location to differentiate the indoor workers from the street workers. Specifically, indoor prostitutes are coded as such if they are either arrested in a hotel/motel or in a residence.

Our main independent variable is *Craigslist Entry*$_{iy}$, which is a binary variable that indicates whether Craigslist is present in county *i* in year *y*. This variable is constructed using information from the Craigslist website, which specifies the locations and years in which new sites are launched.[17] By combining the TER prostitution data with the Craigslist entry information, we are able to contrast pre-entry prostitution figures with post-entry prostitution trends. To account for potential confounding factors that influence prostitution and Craigslist entry in each county, we include demographic, socioeconomic, and crime-related factors as control variables. The U.S. Census Bureau provides county level information on age-group proportions, ethnicity proportions, population size, poverty, employment proportions, and average income levels. FBI's databases provide county level information on various crime trends for each year, and annual number of police employees.

Given that the proportion of sexually active individuals can influence the demand and supply of sexual services, we created the controls for population proportion of age groups 15-19, 20-39, and 40-59, for each county. We also control for the proportion of White, African American, and Asian as these are major ethnic groups having reported representation in the prostitution market (Hughes 2005). We further include population

[17] Collected from http://www.craigslist.org/about/expansion. Accessed on 18 June 2011.

size, as a covariate to account for potential increase in demand and supply of sexual services due to availability of potential participants in each location. The lack of employment, low incomes, and poverty levels can steer individuals towards prostitution (Eisenberg and Lazarsfeld 1938, Monroe 2005). To control for these economic factors, we added the proportion of employed individuals, average annual income, and poverty level as covariates in our model. Finally, the usage of other hookup and dating sites are likely to grow with increasing internet penetration. Also, the prevalence of TER reviews could differ across locations due to differences in internet penetration. To reduce extraneous effects arising from varying levels of internet access, we controlling for the availability of broadband providers using data furnished by the Federal Communications Commission.

We also consider criminology factors that may influence prostitution. We control for number of police employee as the size of the police force is a deterrent against prostitution activities (Weitzer 1999). The FBI database *Law Enforcement Officers Killed and Assaulted* (LEOKA) provides information on the annual number of police employees at each county. Further, extant work has found that non-financial incentives of joining the online sex industry include the need to feel different, to be validated, to be in control, and it is also an alternative to self-harming (Jonsson et al. 2015). These reasons are inextricably related to adverse life experiences and domestic violence. Criminology studies note that organized vice rings have intentionally hook girls on drugs and forced them to work as prostitutes to support their drug habits (Hanna 2002). We account for these factors by controlling for the prevalence of runaways, drug-related crimes, and offenses made against family and children, using data from the FBI. In addition, we extracted the count of commercialized vice, larceny, arson, and burglary for various auxiliary tests. Table 1 provides the descriptive statistics.

Table 1: Summary Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Craigslist Entry	16735	0.071	0.258	0	1
Log (TER: All Years)	16735	0.141	0.616	0	7.662
Log (TER: Active Years)	16735	0.105	0.499	0	6.4
Log (TER: All Years, Using Craigslist)	16735	0.036	0.263	0	4.997
Log (TER: Active Years, Using Craigslist)	16735	0.032	0.235	0	4.344
Log (TER: Reviews, Using Craigslist)	16735	0.054	0.392	0	5.889
Log (FBI Indoor Prostitution)	16735	0.047	0.301	0	5.187
Log (Commercial Vice Crimes)	16735	0.111	0.707	0	7.912
Log (Larceny)	16735	2.866	1.886	0	9.324
Log (Arson)	16735	0.457	0.747	0	6.133
Log (Burglary)	16735	2.117	1.474	0	7.984
Age 15-19 Proportion	16735	0.074	0.013	0.022	0.25
Age 20-39 Proportion	16735	0.236	0.044	0.109	0.496
Age 40-59 Proportion	16735	0.28	0.029	0.103	0.48
White Proportion	16735	0.897	0.156	0.03	1
African American Proportion	16735	0.075	0.14	0	0.867
Asian Proportion	16735	0.007	0.017	0	0.639
Log (Population Size)	16735	9.714	1.224	4.007	14.656
Log (Poverty)	16735	7.671	1.223	0	12.923
Employed Proportion	16735	0.947	0.021	0.697	0.99
Log (Annual Mean Income)	16735	10.486	0.244	0	11.566
Log (Broadband Penetration)	16735	1.446	0.393	0	3.068
Log (Police Officers)	16735	3.331	1.245	0	8.851
Log (Offense Against Family and Children)	16735	1.384	1.415	0	7.559
Log (Runaway Individuals)	16735	0.968	1.33	0	7.445
Log (Drug-Related Crimes)	16735	3.388	1.865	0	9.544

Note. All logged variables are of the format of log (X+1).

4. Empirical Methodology

During the 2000s, Craigslist expanded to different locations in the United States in a staggered fashion, making its site available to a few cities at a time. Because Craigslist ads are location-specific in nature, counties with Craigslist can be seen as ‘treated’ locations since only the local populations are able to access to the services of the escort ads posted on the site. In the same fashion, counties that do not have Craigslist in the same period serve as ‘control’ location. Thus, the phased expansion of Craigslist in the United States represents a natural experiment that allows for the comparison of the difference in prostitution incidence for counties with Craigslist before and after site entry to the same difference for counties that did not experience site entry. We exploit the variation in Craigslist’s entry across counties and years in the natural experiment setup to identify entry effects on prostitution trends. In particular, we estimate a difference-in-difference regression of the form:

$$\ln\left(1 + Prostitution_{iy}\right) = \alpha_i + \beta_y + g \cdot \boldsymbol{\gamma}_{iy} + p \cdot Craigslist_{iy} + e_{iy}, \qquad (1)$$

where *i* indicates counties and *y* refer to year, *y* = 1999, … , 2008; $Prostitution_{iy}$ is the number of prostitutes for county *i* in year *y*; $\boldsymbol{\alpha_i}$ is a vector of 1,796 county fixed effects; $\boldsymbol{\beta_y}$ is a vector of year fixed effects; $\boldsymbol{\gamma}_{iy}$ is a vector of county-year covariates including demographic, socioeconomic, and crime-related factors (i.e., age proportion, racial proportion, population size, employment proportion, income level, poverty level, broadband providers, number of police employees, and various crime trends); $Craigslist_{iy}$ is the binary indicator for Craigslist entry, which equals to 1 if the county has Craigslist in a particular year, and equals zero otherwise; and e_{iy} is error term.

In the above specification, the coefficient *p* is the difference-in-difference estimate of the effect of Craigslist’s entry on the incidence of prostitution. If *p* > 0, then site entry is linked to an increase in prostitution incidence. The county level fixed effects control for time-invariant geographical differences, while year fixed effects control for temporal macroeconomic shocks, which allows for the comparison of prostitution counts between counties over time. To account for serial correlation in the data, we clustered the error terms at the county level (Bertrand et al. 2004). Finally, we tackle heteroscedasticity in population size by weighting our regressions by population size. In our estimations, we use various alternative definitions of indoor prostitutions based on online and offline data sources to see if results would differ qualitatively. Furthermore, given that a single Craigslist entry may sometimes span multiple counties, we check whether the results are stable when the regressions are performed at the Metropolitan Statistical Area (MSA) unit of analysis.

5. Results

5.1 Main Analysis

Table 2 presents the main results for our empirical analysis. First, we show the population weighted OLS regressions in Model 1 using the broadest definition of prostitution incidence, *TER: All Years*. We see that the binary entry variable yields a positive and significant coefficient. This estimate represents a 47.69 percentage increase in prostitution trends due to Craigslist's entry. We repeat this analysis under a MSA unit of analysis and find that the Craigslist entry variable remains positive and significant. In Models 3 and 4, we report the estimation results using a stricter definition of prostitution count, *TER: Active Years,* wherein sex workers are assumed to be active for the years bounded by her first and last review received on TER. Under this stricter definition of prostitution incidence, the site entry coefficients remain positively significant but are of a reduced magnitude. In particular, the effect size of the entry variable reflects a 26.61 percentage increase in prostitution incidence (Model 3).

Next, we further tighten our definition of prostitution incidence by considering only sex workers who have solicited clients on Craigslist. We repeat our previous analyses in Models 5 to 8. We continue to find a positive and significant coefficient for the Craigslist entry variables in these models. In our most conservative definition of prostitution count (Model 7), site entry leads to a 17.58 percent increase in prostitution incidence, representing a smaller effect than its counterpart in Model 3.[18] Finally, we assess if the results remain qualitatively similar under an offline proxy for prostitution count via police arrests. We find that the entry estimates in Models 9 and 10 remain positive and significant, suggesting that the entry effects observed under TER data are not

[18] Using the serial correlation check in Bertrand et al. (2004), we replicated our model 1000 times with randomly assigned pseudo treatments for our strictest model (Model 7). We find that only 6.2% of these models had significant coefficients for the pseudo Craigslist entry when clustered standard errors is used. This number is close to the conventional standard of 5% level of significance which is used to distinguish true results from those that arise by chance. The result of this check indicates that clustered standard errors are able to satisfactorily alleviate serial correlation issues in our study context.

simply driven by increasing reviewing activity on TER over time.[19] As expected, the effect size of Craigslist entry in Model 9 is smaller than those derived under TER data, due to the fact that prostitution cases can go undetected by enforcement agents.

An examination of the coefficients on the covariates reveals some meaningful relationships between socioeconomic factors and prostitution trends. As expected, the regressions show that prostitution increases with population size, poverty levels and broadband penetration, and decreases with employment proportions and average income levels. However, it is surprising to see the number of police officers does not hold a significant relationship with prostitution count. The number of policing resources assigned to a location can be a consequence of crime intensity and can also act as a deterrent to future crime rates. The opposing effects embodied by this variable may cancel each other out, leading to an overall zero effect. Finally, we notice that the number of drug-related arrests is negatively correlated with prostitution incidence under the TER data but is positively related with prostitution arrests from the FBI dataset. This inconsistency might be an artifact of the different datasets utilized. A planned crack-down on drug syndicates may lead to the detection of underlying prostitution activities, resulting in a positive correlation between the frequency of drug-related arrests and prostitution arrests in the FBI data.

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[19] In a separate analysis, we further tracked the annual change in review count for each sex worker on TER over the study period. We find that the annual average number of reviews per worker is not increasing.

Table 2: Main Results on the Impact of Craigslist Entry on Prostitution Levels

	TER: All Years		TER: Active Years		TER: All Years (Using Craigslist)		TER: Active Years (Using Craigslist)		FBI Indoor Prostitution Arrests	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Craigslist Entry	0.390***	0.696***	0.236***	0.457***	0.199***	0.334***	0.162***	0.287***	0.047***	0.105***
	(0.04)	(0.08)	(0.03)	(0.07)	(0.03)	(0.06)	(0.03)	(0.05)	(0.02)	(0.03)
Age 15-19 Proportion	9.834***	4.609	6.712***	3.205	6.832***	8.675*	5.869***	8.343*	0.745*	-7.499***
	(1.49)	(6.35)	(1.12)	(5.28)	(1.17)	(4.92)	(1.02)	(4.55)	(0.40)	(2.72)
Age 20-39 Proportion	1.310*	-0.145	1.054*	0.486	1.005**	2.325	0.847**	2.128	-0.339	-4.228***
	(0.78)	(2.65)	(0.60)	(2.19)	(0.47)	(2.17)	(0.40)	(2.03)	(0.22)	(0.98)
Age 40-59 Proportion	1.467*	2.829	1.221**	2.486	1.457***	3.999	1.272***	3.899*	-0.228	-2.686*
	(0.82)	(3.13)	(0.61)	(2.69)	(0.50)	(2.51)	(0.43)	(2.35)	(0.19)	(1.42)
White Proportion	-6.695***	-0.005	-4.951***	-1.696	-4.476***	-5.190	-3.939***	-5.640	-1.201**	2.643
	(2.22)	(7.04)	(1.65)	(5.13)	(1.41)	(4.32)	(1.23)	(3.64)	(0.48)	(3.22)
African American Proportion	-2.353	6.177	-1.843	3.544	-2.122	-1.310	-1.872	-2.377	-0.299	6.396**
	(2.12)	(6.83)	(1.57)	(4.81)	(1.31)	(4.11)	(1.14)	(3.44)	(0.43)	(3.08)
Asian Proportion	4.585	3.820	2.874	0.199	2.094	-1.878	1.577	-2.536	1.034	2.062
	(5.30)	(7.76)	(4.01)	(4.90)	(3.52)	(4.35)	(3.11)	(3.57)	(0.94)	(2.25)
Log (Population Size)	1.057***	0.412***	0.710***	0.328**	0.434***	0.117	0.373***	0.119	0.110**	0.270***
	(0.23)	(0.16)	(0.17)	(0.15)	(0.14)	(0.10)	(0.12)	(0.09)	(0.05)	(0.07)
Log (Poverty)	0.223***	-0.026	0.138***	-0.057	0.046	-0.031	0.033	-0.049	0.046*	0.090
	(0.06)	(0.12)	(0.04)	(0.10)	(0.03)	(0.08)	(0.03)	(0.07)	(0.02)	(0.08)
Employed Proportion	-1.324***	-6.758***	-1.115***	-6.261***	-0.935***	-4.214***	-0.847***	-4.096***	-0.184	0.183
	(0.48)	(1.98)	(0.38)	(1.65)	(0.28)	(1.47)	(0.25)	(1.33)	(0.15)	(0.71)
Log (Annual Income)	-0.138**	-0.047	-0.091**	-0.027	-0.022	0.024	-0.018	0.028	-0.040	-0.108
	(0.06)	(0.08)	(0.04)	(0.06)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)	(0.08)
Log (Broadband Penetration)	0.310***	0.850***	0.249***	0.716***	-0.002	0.130*	0.007	0.131*	0.003	0.056
	(0.04)	(0.13)	(0.04)	(0.11)	(0.02)	(0.08)	(0.02)	(0.07)	(0.01)	(0.04)
Log (Police Officers)	-0.018	0.091	-0.016	0.076	-0.023	0.062	-0.020	0.046	-0.007	0.005
	(0.03)	(0.12)	(0.02)	(0.09)	(0.02)	(0.07)	(0.02)	(0.06)	(0.01)	(0.06)
Log (Offense Against Family and Children)	0.000	0.022	-0.001	0.016	0.001	0.018	0.001	0.015	0.001	-0.009
	(0.01)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Log (Runaway Individuals)	0.001	0.017	0.003	0.017	-0.002	0.008	-0.001	0.010	0.001	0.002
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Log (Drug-Related Crimes)	0.001	-0.073**	-0.002	-0.070**	0.001	-0.031**	0.000	-0.032**	0.012**	0.047**
	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)	(0.00)	(0.01)	(0.01)	(0.02)
Unit of Analysis	County	MSA	County	MSA	County	MSA	County	MSA	County	MSA
R-squared	0.260	0.443	0.186	0.349	0.127	0.269	0.139	0.247	0.028	0.201
F-Stats	14.027	11.053	9.249	6.935	5.847	4.461	5.057	3.830	2.246	2.629
Observations	16735	4898	16735	4898	16735	4898	16735	4898	16735	4898

Note. The dependent variables for Models 1-8 are the log number of TER prostitution cases under various definitions. The dependent variables for Models 9 & 10 are log number of FBI indoor female prostitution arrests cases. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All models are estimated with county and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Robustness Checks

We further scrutinize the main results under a set of robustness checks. Taking a conservative stance, we adopt counts of sex workers who are known to solicit on Craigslist for all our subsequent analyses. Results for the robustness checks are reported in Models 2 to 6 of Table A2. We replicate the respective estimates from the main model in Model 1 for comparison purposes. First, we rerun the main specification using un-weighted regressions to examine whether the main effect persist without population weights. In Model 2, we find that the Craigslist entry variable continues to have positive and significant coefficients under the un-weighted specification. Second, to abstract from scaling issues, we run the analysis using prostitution counts that are normalized by population size.[20] We report estimates for this regression in Model 3. Third, to allow for a more comparable set of counties to be used in our difference-in-difference analysis, we restrict our analysis to a sample of counties which have at least one count of prostitution taking place during the study period. We report this result in Model 4. Fourth, we include time-varying county-specific controls in our main specification to account for the possibility of location-specific time trends, and report this result in Model 5. The site entry estimates in these models continue to be positive and significant. Fifth, we rely on review counts to supplement the number of profiles as an alternative dependent variable, as it proxies for the incidence of prostitution activity. As seen in Model 6, the regression

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[20] Specifically, our dependent variable is normalized as follows: $log\left(10{,}000 \times \frac{Prostitution+1}{Population+1}\right)$. The resultant coefficient gives the percentage increase in sex workers per 10,000 people upon site entry.

shows that Craigslist entry leads to an increase of 29.69% in prostitution activity, as measured by review count.

Sixth, we conduct our analysis on a county-month level to see if the results hold at a finer unit of analysis. Our results for this analysis are reported in Table 3. For this analysis, we applied a "regression discontinuity" modeling approach, and aggregated the observations into two periods: before and after site entry (Manchanda et al. 2015). The approach compares log of total prostitution counts before website entry with that after site entry. Further, we consider consecutively longer temporal windows on both sides of the site entry treatment, to which the entry month is left out as the reference point. The temporal windows range from one month to seven months in length, as we look for the starting month for the site entry effect to start showing. When we compare the coefficients from Model 1-7, we find that as the time-duration of the windows get longer, the magnitude of Craigslist impact seems to increase. Further, the result reveals that the impact of Craigslist tends to start from the fifth month after Craigslist's launch (Model 5 of Table 3).

Table 3: Analysis of Craigslist's Impact using Monthly Data

	Before & After Models (with County fixed effects)						
	1 month Window Length	**2 months Window Length**	**3 months Window Length**	**4 months Window Length**	**5 months Window Length**	**6 months Window Length**	**7 months Window Length**
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Craigslist Entry	0.004	0.003	0.010	0.017	0.029**	0.040***	0.052***

Note. Dependent variable is TER: Active Years (Using Craigslist). Months are coded as 0 for pre-entry and 1 for the post-entry. Models 1 through 7 report results under different window lengths. Robust standard errors clustered by counties are used. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Seventh, we also rely on various matching estimation techniques to arrive at a set of treated and control counties that are statistically similar in terms of the demographic, socioeconomic and crime indicators to see if the main results continue to hold. All control variables are used in the matching procedure. In our matching, we have restricted the analysis to observations that have common support.[21] We first report the covariate balance checks under the one-to-one matching scheme without replacement (Table A3). All covariates had a reduction in bias, and majority of matched covariates show a reduction in bias by over eighty percent.[22] Further, the two-sample t-test for equal means suggests that the means are statistically similar for all covariates between treated and control groups after matching. We attempted various matching schemes including k-nearest neighbor, kernel matching, and coarsened exact matching.[23] While many of our estimates in Table A5 are of a smaller magnitude than the baseline estimates in Table 2, the matched estimates remain positive and significant, indicating that the observed entry effect on prostitution is not driven by peculiar local characteristics in certain locations.

Finally, we account for the possibility of duplicate TER profiles by assessing the change in effect size when TER profiles with different review count cutoffs are

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[21] A plot of the propensity score distribution (Figure A2) shows that there is a good amount of overlap between the treated and control unit, thereby satisfying the common support assumption.

[22] Table A4 provides the coefficient estimates for the covariates that predicted site entry in the matching scheme.

[23] We utilized different choices for nearest neighbor, i.e. 1, 2, 3, or 4 neighbors, and our choice of kernel bandwidths ranges from 0.06 to 0.0001.

considered. Sex workers might abandon an existing profile and start a new profile if the existing one has received bad reviews. Such an act is more likely to take place when the existing profile only has few reviews, as it is more costly for a worker to abandon a profile that has accumulated multiple reviews. We conduct regressions using dependent variables with different review count cutoffs, under the assumption that profiles with a greater number of reviews are more likely to represent actual, active sex workers. The coefficient sizes of each of these models and that for the original baseline model are plotted in Figure A3. We find that the effect size generally drops as the cutoff value increases. However, we find that the coefficient stabilizes at around 10% for sex workers who have 6 or more reviews. Given that the effect does not disappear with stricter definitions of an "active" worker profile, the observed positive entry effect on prostitution is deemed to be robust against the possibility of duplicate profiles.

5.3 Entry Exogeneity

In order for the results above to be valid, the entry of Craigslist needs to be exogenous with respect to prostitution trends. Several aspects of Craigslist's operation suggest that its entry decisions are uncorrelated to the local prostitution trends. First, Craigslist did not charge its users for posting and accessing prostitution ads prior to 2009, the point when they received public complaints. The site relied on fees from job postings and New York City apartment listings to offset its operational costs. Thus, Craigslist did not have a profit motive to launch in locations with existing prostitution trends, as it does not receive any financial gains from ads posted in the erotic/adults service section (Stannard 2008).

Second, as a classified advertisement portal, Craigslist hosts multiple ad sections including jobs, housing, items for sale, and services. As such, the decision to enter a location is unlikely to be driven solely by the local demand for online solicitation. However, it is plausible that the growth of cities may indirectly lead to a simultaneous increase in both prostitution demand and user requests for Craigslist service. We address for this possibility by controlling for a wide variety of socioeconomic factors that capture the economic characteristics of each location in our main regressions above. In addition, we empirically assess whether the entry of Craigslist is predicted by the prevailing volume of prostitution activity in each county. To do so, we regress Craigslist entry on the existing prevalence of prostitution, along with the same set of demographic, socioeconomic, and crime-related factors used in the main analysis. The dependent variable, Craigslist entry, is made up of a string of zeros and is terminated with the value of one in the first year of entry in each county. Subsequent years after site entry are not included in the regression analysis as the goal here is to identify whether existing prostitution levels correlate with entry patterns. We used three different measures of prostitution levels in our analysis. The first two measures are the number of prostitutes who used Craigslist for solicitation under the definitions of *TER: All Years* and *TER: Active Years*, as described earlier. We also rely on the number of commercial vice crimes as a third measure of prostitution activity, because organized prostitution rings may influence the entry of Craigslist into counties that were deemed to be appropriate locations for supporting their prostitution business. The results of this analysis showed that all three measures of prostitution levels do not correlate with entry patterns of Craigslist (Table A6), suggesting that the exogeneity assumption is reasonable.

Third, the staggered pattern of site entry in various United States locations pertains uniquely to Craigslist. Given Craigslist's unique entry pattern is dissimilar to the entry patterns of alternative prostitution sites, our difference-in-difference coefficient would be picking up site entry effects that pertain strictly to Craigslist. Furthermore, we rely on counts of prostitutes known to solicit on Craigslist to reduce concerns of the entry variable picking up effects from other prostitution sites. Moreover, many of these solicitation sites charged users a fee for posting and/or accessing the escort ads, which led to lower web traffic for these sites. Thus, Craigslist, being one of the first online platforms that facilitate sexual solicitation, dominated the online prostitution market in the early and mid-2000s.[24] While the presence of alternative prostitution sites may potentially adds noise to the estimates, the relatively small traffic volume with respect to Craigslist's site visits is unlikely to distort the overall impact of Craigslist's entry on prostitution trends. Regardless, we perform additional empirical checks to assess whether these alternative sites would confound our estimated entry effect. Our test involves adding the entry times and web traffic of alternative sites as covariates, and assessing whether that affect the main results.

We consider two scenarios in which alternative platforms could potentially affect the impact of Craigslist on the online prostitution market. First, competing sites may enter different locations in a staggered fashion similar to Craigslist's entry style. Entry patterns of the alternative site may be correlated to the entry patterns of Craigslist as these sites face similar operation considerations. To our knowledge, Backpage is the only

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[24] From Google search data, we see that the search traffic for Backpage and Eros (the two most popular adult sites after Craigslist), were approximately 1/45 and 1/15 of Craigslist's search volumes between year 2004 and 2008, respectively (Accessed on April 25, 2017).

other classified ad site that also operated during the study period, and had hosted prostitution ads. The second scenario involves solicitation sites that made its service simultaneously available to all locations via a single entry time. While the time fixed effects in our baseline model should take care of the impact of such solicitation sites, we devised a separate empirical test involving site traffic data to rule out any further concerns related to such sites. In particular, we consider Eros.com, the largest solicitation site that was made available to all location via a single launch date. Results of the two conducted tests are presented in Table 4. Both location and year fixed effects are used in these analyses. Collectively, these two tests provided additional confidence that the presence of alternative solicitation sites do not distort the main results.

Table 4: Accounting for Alternative Prostitution Sites

	Main Model	**Controlling for Backpage Entry**	**Controlling for Eros Entry**	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Craigslist Entry	0.162*** (0.03)	0.111*** (0.02)		
'Craigslist' search term			0.005*** (0.00)	
'Eros' search term			-0.001 (0.00)	
Log ('Craigslist' search term)				0.049* (0.03)
Log ('Eros' search term)				-0.040 (0.03)
R-squared	0.139	0.207	0.192	0.181
F-Stats	5.057	5.349	6.997	6.448
Observations	16735	16735	2210	2210

Notes. We collected data on Backpage entry by scraping Backpage sites of various counties, and noting the first year in which ads became available. We include Backpage's entry as a control in our baseline model. Model 1 reports Craigslist coefficient that was mentioned in Model 7 of Table 2. Model 2 reports coefficient for Craigslist entry after controlling for Backpage entry. Given that Eros entered all locations at the same time, we contrast the impact of search traffic from both sites over time on our outcome variable. Search traffic can serve as a good approximation for the average site visit count and usage level for the solicitation sites. We collected search trend data from Google Trends based on the keywords 'craigslist' and 'eros' for the years 2004 to 2008. Search volumes of keywords are available from 2004 onwards, allowing for analysis to cover the 2004-2008 period. These search volumes are available by the MSA-month level. The dependent variables for all models are the log number of TER prostitution cases for active years and using Craigslist. The same set of control covariates, and location and time fixed effects from Table 2 are used in all models. Robust standard errors clustered by location are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

5.4 Falsification Results

To assess the possibility of the entry variable picking up significant effects spuriously, we perform two falsification tests. First, we repeat our analysis using alternative crimes that are unlikely to bear any relationship with the entry of Craigslist and/or prostitution trends, as dependent variables. Specifically, we choose *larceny*, *arson* and *burglary* as alternative dependent variables because these crimes tend to occur spontaneously and/or are unlikely to be mediated through Craigslist sites. Under this falsification check, we expect the site entry coefficients not to pick up any effect on these crimes in these regressions. A significant estimate on the Craigslist variable in these tests suggests the presence of spurious correlation in our main analyses. Results of the falsification tests are depicted in Table A7. It is observed that binary entry variable do not hold statistically significant relationships with the incidence of larceny, arson, or burglary, providing supporting evidence that the entry effect on prostitution levels did not arise spuriously.

Second, the relationship between Craigslist's entry and prostitution incidence may be driven by unobserved factors that are confounded with prostitution trends. For instance, changes in the macro-economic conditions or the expansion of prostitution rings in certain locations can increase the prevailing local prostitution trends, which can subsequently lead to requests for Craigslist launches in these areas to facilitate solicitation. Under such a possibility, prostitution incidence may already be increasing due to these alternative reasons, and would continue to increase even without the presence of Craigslist. In these cases, the entry variable is merely picking up these pre-existing effects caused by confounding factors. We assess the possibility of such pre-entry trends by running a time falsification check that includes three years of pre-entry indicators as placeboes, along with four years of post-entry indicators to capture the inter-temporal entry effects as follows:

$$\ln(Prostitution_{iy}) = \alpha_i + \beta_y + g \cdot \boldsymbol{\gamma}_{iy} + \sum_j p_j \cdot Craigslist_{iy}^{j} + e_{iy}, \qquad (2)$$

where $j \in \{-3, -2, -1, +1, +2, +3, +4\}$ and year y is the j^{th} year since Craigslist's entry in county i. In the presence of a pre-entry effect, the placebo indicators would produce positively significant coefficients. In addition, the coefficients of the post-entry indicators reflect the change in effect sizes over time. We conduct this check using the stricter definition of prostitution incidence, i.e., *TER: Active Years (Using Craigslist)*.[25] Results of this falsification tests is reported in Figure 1.[26] Across all models, we observe that the three year pre-entry placebo variables do not hold significant coefficients, suggesting that the parallel trends assumption is fulfilled and that the observed relationship between prostitution levels and Craigslist entry is unlikely to arise as an artifact from events that occur in periods prior to Craigslist's entry. The result of the time falsification check also lends support to the exogeneity assumption by showing that site entry is not correlated with pre-existing increases in prostitution levels. The entry indicators are positively significant for post entry periods and are increasing with time. In particular, the entry

[25] Alternative prostitution definitions provided qualitatively similar estimates.

[26] Figure 1 reports three pre-entry and four post-entry years. In addition to this specification, we also tried other models involving different number of leads and lags. Results consistently show that the pre-entry effects are not present and that significant estimates are only present in the post-entry periods. Results of these additional checks are available upon request.

effects exhibit a non-linear impact on the prostitution growth, corresponding to an increase of over 200 percentage point in the fourth year of entry.

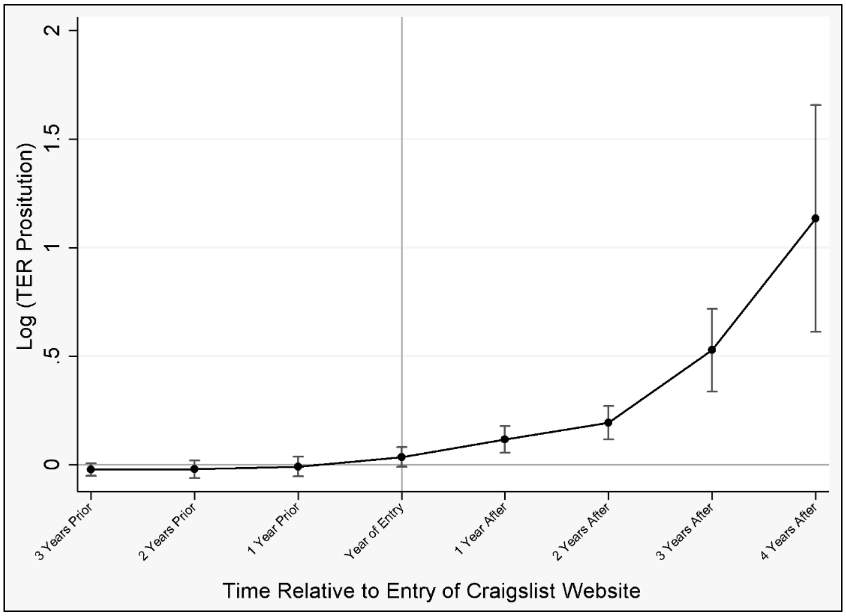

Figure 1: Impact of Pre- and Post- Entry Craigslist Indicators (95% confidence level)

Note: The more conservative definition of prostitution incidence is used in the derivation of this graph. That is, TER: Active Years (Using Craigslist). The alternative definition, TER: All Years (Using Craigslist) produces a similar graph.

6. Potential Mechanisms and Related Trends

From the analyses thus far, results suggest that the entry of Craigslist has an effect of increasing the prostitution incidence of locations that it enters. However, it is less clear what underlying mechanisms are driving this relationship. Here, we perform five analyses to shed light on some related mechanisms.

6.1 Relationship with Commercial Vice

It is important for policy makers and enforcement agencies to understand whether the Craigslist-enabled prostitution is operated mainly by organized vice groups or by freelance sex workers, since the legal considerations for curbing prostitution of each type are different. To address this dichotomy in possibilities, we assess and compare the Craigslist's impact on prostitution across locations with varying levels of organized prostitution activity. To do so, we regress prostitution count on commercial vice activity, Craigslist's entry, and their interaction, along with the same set of controls and fixed effects in our main models. In this regression, the coefficient of Craigslist entry indicates the effect of site entry on prostitution, in locations where organized vice activities are low or absent. As the commercial vice variable captures the prostitution levels in areas operated by commercial vice groups, the Craigslist entry variable now measures the market size of sex workers who are likely to operate independently from the organized rings. The interaction term indicates the increase in prostitution that occurs in areas with Craigslist presence and high commercial vice activity.[27] Since not all commercial prostitution activities are detected by enforcement agencies, the volume of these organized crimes may not be precisely documented by the FBI. To alleviate this concern, we conduct a robustness check in which we adopted an alternative definition for commercial vice. In this check, we abstract away from the counts of commercial vice activity by indicating whether commercial vice activity is present or absent in each county-year.

Table 5 reports the results of this analysis. Across all models, we see three trends. First, the estimate on Craigslist entry is positive and significant, signifying that independent sex workers do operate on Craigslist. Second, we note that the interaction

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[27] The interpretation of results builds on the rationale that online prostitution that takes place in locations with commercial vice activity are likely to involve organized vice groups.

term is positively significant, indicating that the increase in prostitution incidence occurs in site entry locations that have commercial vice activities. These two findings jointly suggest that the prostitution market enabled by Craigslist is made up of both independent sex workers and prostitutes working under commercial vice organizations. A comparison of these coefficient sizes suggest that the prostitution by commercial vice groups are at least two times larger than that made up by independent providers. Third, the commercial vice variable holds a negative estimate, indicating that counties with commercial vice activity but no Craigslist presence are experiencing a drop in prostitution activity. Such a trend is reflective of a shift from street prostitution to online prostitution.

Table 5: Involvement of Commercial Vice on Craigslist-Enabled Prostitution

	TER: All Years (Using Craigslist)		**TER: Active Years (Using Craigslist)**	
	Counts of Com. Vice Activity	**Binary Indicator for Com. Vice Activity**	**Counts of Com. Vice Activity**	**Binary Indicator for Com. Vice Activity**
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Commercial Vice	-0.075*	-0.154***	-0.066*	-0.130***
	(0.04)	(0.05)	(0.04)	(0.04)
Craigslist Entry	0.079***	0.091***	0.059**	0.071***
	(0.03)	(0.03)	(0.02)	(0.02)
Craigslist Entry ×	0.201***	0.711***	0.172***	0.597***
Commercial Vice	(0.02)	(0.09)	(0.02)	(0.09)
R-squared	0.258	0.226	0.236	0.204
F-Stats	13.319	7.711	10.737	6.446
Observations	16735	16735	16735	16735

Note. All dependent variables are the log number of prostitution cases from TER that are known to utilize Craigslist in their solicitation. For Models 1 and 3, the counts of commercial vice activity are log-transformed, while the commercial vice variable for Models 2 and 4 are binary indicators. Robust standard errors clustered by counties are reported in parentheses. All control variables and fixed effects reported in Table 2 are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Geographic Trends

To examine the growth patterns of online prostitution, we repeat our main analysis on subsamples of counties with and without prior history of prostitution before site entry.

Prostitution history is based on whether a county has existing prostitutes that are documented on the TER site. In Models 1 and 2 of Table 6, we find that Craigslist's entry has a positive and significant impact on prostitution trends for both counties that have and do not have a pre-existing trend of prostitution. We find that the impact of Craigslist on prostitution tends to be stronger for counties with pre-existing prostitution trends (18.88% increase in Model 2) compared to locations that do not (11.29% increase in Model 1). This set of results is consistent with the theory positing that transacting parties of prostitution tend to conjugate spatially such that search costs for locating each other are reduced. However, the results also indicate that Craigslist, as a platform, also facilitates the new prostitution cases in areas that do not have a history of prostitution. Such a finding is also reasonable when we consider that online solicitation reduces the likelihood of detection and legal persecution, which can lead individuals at the boundary of participation to enter the market when discreet forms of transaction become available.

Table 6: Geographical Trends Related to Prostitution Increase

	Presence of Existing Prostitution		**Spillover Effects**	
	No Prior Trends	**Has Prior Trends**	**Counties with Site Entry**	**Neighboring Counties without Site Entry**
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Craigslist Entry	0.107*** (0.02)	0.173** (0.08)	0.163*** (0.04)	0.129*** (0.03)
R-squared	0.107	0.540	0.240	0.192
F-Stats	3.805	11.312	7.655	5.770
Observations	16046	689	761	761

Note. The dependent variables are the log number of prostitution from TER known to solicit on Craigslist under the Active Years (using Craigslist) definition. Robust standard errors clustered by counties are reported in parentheses. All covariates and fixed effects reported in Table 2 are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Spillover Effects

Many small and mid-sized cities do not have a dedicated Craigslist site serving its locale. Thus, it is possible for sex workers and clients residing in locations without Craigslist to rely on sites from a neighboring location to set up arrangements for sexual transactions. Under this possibility, the entry of Craigslist to a major city may lead to spillovers of increased prostitution incidence in neighboring locations. To test for a spillover effect, we first identify a set of county-pairs in which one of the counties has Craigslist and the other does not (details provided in Appendix 3). We run two separate regressions in our newly derived sample. In the first regression, we regress prostitution incidence on Craigslist's entry for counties that have experienced site entry. In the second regression, we regress prostitution incidence of the neighboring county on the same Craigslist entry variable, along with all covariates associated with the neighboring county. In the case of a spillover effect, the Craigslist variable would show positive and significant coefficients in both models. Table 6 reports results of this analysis.

We find a positive and significant impact of Craigslist's on prostitution incidence for counties that experience site entry in Model 3. In Model 4, we find that the impact of Craigslist's entry also holds a positive and significant impact on prostitution incidence in the adjacent county without Craigslist. A comparison of the estimates further indicates that the magnitude of the spillover effect is smaller (12.9% in Model 4) than the main effect (16.3% in Model 3). This is reasonable given that neighboring counties without site entry tend to be smaller cities relative to the focal county with site entry, which are characterized with smaller markets.

6.4 Types of Sexual Services

The growth of online prostitution stemming from Craigslist entry may be made up of an increase in niche sexual services (e.g., sadomasochism and sex with transgender providers) that are otherwise hard to locate without online intermediation. Using the attributes of sex workers reviewed on TER, we identify and tabulate the frequency of prostitutes providing the following services, namely escort, massage, S&M, and transsexual. To assess whether site entry lead to an increase in workers that provide niche sexual services, we first measure the impact of Craigslist on the incidence of S&M and transsexual services. The increase in these exotic services is further contrasted with the increase in prostitutes who only offered traditional sexual services (i.e., escort and massage), so as to gain an understanding towards the relative increase in across these services. We report the regression results in Table 7.

Table 7: Types of Sexual Services

	S&M / Transsexual	Escort / Massage
Variables	**Model 1**	**Model 2**
Craigslist Entry	0.061***	0.143***
	(0.01)	(0.02)
R-squared	0.082	0.128
F-Stats	2.898	4.399
Observations	16735	16735

Note. The dependent variables are the log count of prostitutes from TER known to solicit on Craigslist. These counts are tabulated by the types of sexual services provided. For Model 1, we include workers in the count as long as they provide either S&M or transsexual services. For Model 2, we include workers who provide only escort and massage services, since these are basic services that are provided by almost all workers. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All control variables and fixed effects reported in Table 2 are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We find that Craigslist entry lead to an increase in sex workers who offers exotic sexual services. With the entry of Craigslist, providers offering these niche services have increased by 6.28 percent, and sex workers who provide solely traditional sexual services have increased by 15.37 percent. While the increase in prostitution is largely constituted by workers who provide traditional sexual services, we find that site entry has also led to a sizable increase in workers who provided niche services. In particular, the increase in workers who provided niche services is about 40 percent of the gain in workers who perform only traditional services.

A related sub-question involves understanding how prostitution trends increase with the availability of an online platform. Specifically, the introduction of the Craigslist site could increase the number of solicitations from existing sex workers, and it could also increase the number of new workers entering the market. To investigate the first possibility, we rely on the number of reviews of existing workers (profiles that are on TER for at least two years) as a dependent variable to proxy for the number of prostitution instances. Results in Model 1 (Table 8) shows that the Craigslist entry indicator holds a positive and significant coefficient, suggesting that the presence of the site does increase the incidence of solicitations of existing workers. We investigate the second possibility by utilizing the number of new TER profiles in each county-year as a dependent variable to proxy for number of new market entrants. This analysis helps to supplement the earlier results derived under the outcome variables which considers both existing and new workers (i.e., entire market size). Model 2 shows that site entry also has a positive impact on attracting new market entrants.

Table 8: Impact on Existing and New Sex Workers

Variables	Number of Reviews for Existing Sex Workers Model 1	Number of New Sex Workers Model 2
Craigslist Entry	0.152*** (0.03)	0.127*** (0.02)
R-squared	0.081	0.109
F-Stats	3.157	4.135
Observations	16735	16735

Note. Dependent variable for Model 1 is log number of TER reviews for existing sex workers. Dependent variable in Model 2 is log number of new TER sex workers who are using Craigslist. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All control variables and fixed effects reported in Table 2 are included. * p < 0.10, ** p < 0.05, *** p < 0.01.

6.5 Policing Efficacy

Law enforcement has relied on Craigslist to locate sex workers and plan sting operations. An understanding of the relative impacts that Craigslist has on facilitating prostitution acts and enhancing policing efficiency provides insight on whether the shutdown of Craigslist's "Adult services" section is justified. We contrast the impact of Craigslist entry on the incidence of prostitute reviewed on TER and the number of indoor female prostitutes arrested. Specifically, we juxtapose the entry coefficients for prostitution arrests on the time falsification results that were previously derived from Figure 1.

In Figure 2, we note the post-entry coefficients for prostitution arrests increase in magnitude over the years, indicating that policing efforts in curbing prostitution trends are enhanced after Craigslist entry. Specifically, we find that the effect sizes grow from 4.71 percent in the first year of entry to 47.54 percent in the fourth year of site entry. However, the gap in growth rate between prostitution incidence and police arrests widens over time, as the coefficients derived under the TER-based definition of prostitution increased from 12.52 to 211.08 percent within the four years of site entry. This indicates that the efficacy gained in police arrests is much smaller than the increase in prostitution enabled by the site.

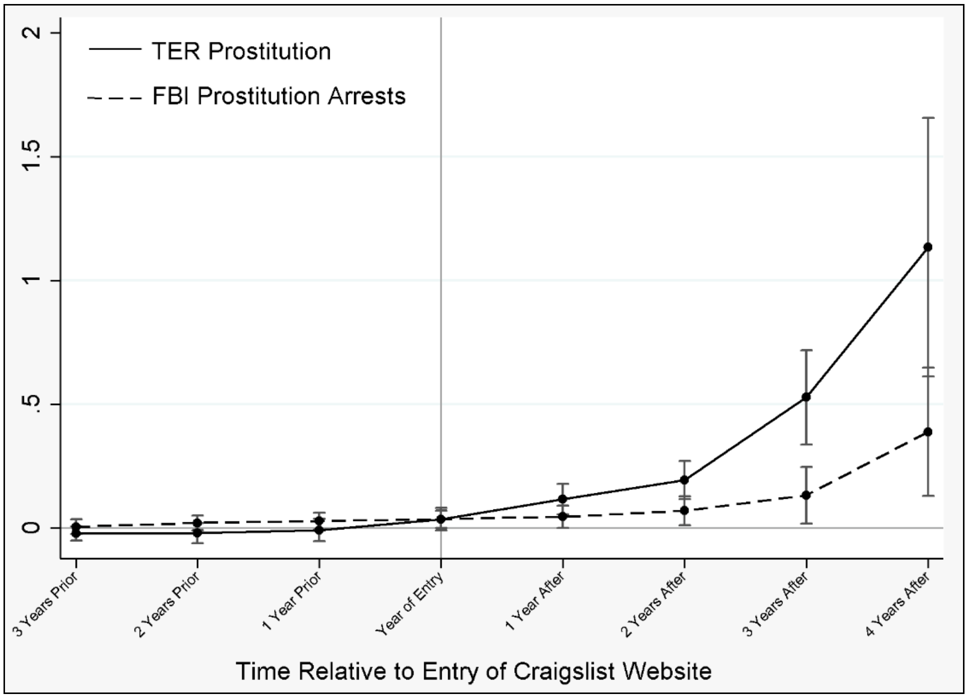

Figure 2 - Impact on Prostitution Incidence and Arrests (at 95% confidence level)

Note: Prostitution count under the definition of TER: Active Years (Using Craigslist) is used to plot the graph involving TER prostitution incidence. Prostitution Arrests under the FBI data is used to plot the other graph**.**

6.6 Relationship across Ad Types

News reports have documented that sex workers have used the *casual encounters* section within 'Personals ads' to post prostitution ads in the effort to generate more business leads (Alban 2005). In addition, men who are originally looking for non-paid hookups in the "Personals" section may move towards the erotic service listings in search for niche sexual services provided by sex workers. Interestingly, through self-reports, we note instances of female users who initially look for dates in the "Personals" section may later post ads in the erotic listings section to make some extra cash while having casual hook ups (Segura 2007). Given these observations, we seek to examine the underlying economic relationship between these two ad types on prostitution levels.

To this end, we collected data on the number of ads in each section and use that as regressors in the main models. For this analysis, the count of Personal ads includes casual encounter ads, and heterosexual ads (i.e., M4W and W4M), since TER sex worker profiles are all females that serve male clients. We enter each of these regressors separately into the main models to understand their basic relationship with prostitution count. To assess the economic nature between these two ad types, we further add both regressors, along with their interaction term in the same model to check the signs of their coefficients. In Models 1 and 2 of Table 9, we see that erotic sex ads and casual sex ads both exhibited a positive and significant impact on prostitution levels. In Model 3, we find that the interaction terms between the erotic service ads and the personal ads is positive and significant, indicating a complementary effect between the erotic service ads and the personals ads on prostitution incidence.

Table 9: Impact of Erotic and Casual sex ads on Prostitution

Variables	**Model 1**	**Model 2**	**Model 3**
Log (Erotic sex ads)	0.083*** (0.02)		-0.098 (0.06)
Log (Casual sex ads)		0.074*** (0.02)	0.055 (0.04)
Interaction Term			0.014** (0.01)
Time-varying County-Specific Controls	✓	✓	✓
R-squared	0.489	0.491	0.492
F-Stats	11.089	10.885	10.929
Observations	4403	4403	4403

Note. All dependent variables are Log (TER: Active Years, Using Craigslist). All covariates in the main model are included here. In Model 1, erotic sex ads includes ads from erotic services section (or adult services section) of Craigslist. In Model 2, casual sex ads include Craigslist's *personals* section ads, like men for women (m4w) ads, women for men (w4m) ads, and casual encounter ads from Craigslist. Robust standard errors clustered by metropolitan statistical areas (MSA) are reported in parentheses below coefficient values. All control variables and fixed effects at MSA and year levels reported in Table 2 are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7. Discussion and Implications

In this paper, we study the link between Craigslist's entry and prostitution trends, and uncovered a positive impact of site entry on prostitution trends. In our analysis, we exploit the exogenous entry of Craigslist via a difference-in-difference setup to estimate the site entry effect on prostitution incidence. We find that this relationship persists across various robustness checks. Falsification tests suggest that this observed relationship did not arise spuriously. On top of the main relationship, we also performed six sub-analyses, to uncover the mechanisms underlying the phenomenon, including the relationship with respect to commercial vice, geographical trends, spillover effects, sexual services, policing efficacy, and different ads.

Our study holds several implications for various stakeholders, including policy makers, site owners, enforcement agencies, and academics. First, our study provides new inputs for policy makers and site owners. Based on conservative model estimates, we find that Craigslist entry, on average, is linked with a 17.58 percent increase in annual prostitution incidence at a county.[28] If we were to consider counties that have at least one incidence of prostitution, an 18% increase represents a gain of approximately one prostitute in a county-year. Despite this modest increase in actual count, the reported effect grows exponentially over time, and can culminate to a 211 percent increase within four years. This rapid growth in prostitution levels should not be ignored. Moreover, the effect size unveiled in our estimations is likely just the tip of the iceberg of the actual

[28] In raw numbers, a 17.58% increase means that average prostitution levels would increase to 0.18 workers in a county-year. This modest impact is due to the low average prostitution: many county-years have zero prostitution.

impact. Given that the true impact of Craigslist on prostitution incidence is likely to be greater than our reported estimates, the uncovered relationship serves to affirm the soundness of the decisions made to intervene in the operation of platforms that facilitate prostitution. In addition, our study findings add to the ongoing policy debate of making website owners legally responsible for criminal acts that are facilitated through their sites.[29] Despite sentiments against the regulation of websites on the basis of protecting freedom of speech (Lee 2013), additional clauses to the dated CDA should be considered to account for circumstances where sites are clearly fostering criminal acts. Evidently, the self-governance model does not work, as our study results demonstrate that users are capitalizing on the lack of regulation to participate in online prostitution.

Second, our finding on the involvement of organized vice groups with prostitution on Craigslist highlights the socio-legal concerns related to the introduction of online platforms. This issue is especially pressing given that the majority of the prostitution facilitated by Craigslist is likely induced by organized vice groups as opposed to voluntary prostitution. Given the organized prostitution operations tend to co-exist with sex trafficking (Schauer and Wheaton 2006), an increase in Craigslist-based prostitution in locations with commercial vice activities is likely linked with an increase in sex trafficking. The presence of an online venue to facilitate prostitution can drive up demand for paid sexual services, which induces vice organizations to increase their sex trafficking

[29] As of August 2017, a new bill against online sites that facilitate sex trafficking, Stop Enabling Sex Trafficking Act (SESTA) is introduced in the Senate. See https://www.recode.net/2017/8/1/16074808/facebook-google-amazon-sex-human-trafficking-congress-section-230.

efforts, leading to greater exploitation of vulnerable populations into the sex trade (Hanna 2002). Additionally, prostitution is linked to the proliferation of other illicit activities, namely drug trafficking and drug abuse, which feeds the sex trade. In sum, forced prostitution facilitated by online platforms can lead to a host of other criminal and illegal activities, which are highly damaging social consequences.

While criminals are quick on tapping online capabilities to engage in prostitution, policing agencies have not caught up with the use of online affordances to keep illicit activities in check. While Craigslist-enabled prostitution has grown exponentially, the efficacy gained in prostitution arrests after site launch is at best modest. To address the gap between crime growth and enforcement effectiveness, the realignment of policing resources from an offline-heavy allocation scheme to one that balances allocation across online and offline modes is needed. By tracking illicit activities online and cracking these perpetrators, legal enforcement can deter crimes by raising the costs to make illicit transactions online.

Third, our findings provide insights on the growth pattern of online prostitution. Our analyses indicate that Craigslist entry is likely to increase prostitution in all geographies regardless of existing prostitution, though a greater increase is found in locations with existing prostitution. Moreover, the impact of Craigslist on prostitution is not limited to locations that experience site entry, but can spill over to neighboring cities not served by the platform. At the same time, the growth of prostitution enabled by Craigslist manifest in two ways: 1) increases transactions of existing workers, and 2) attracts new market entrants. These insights have specific implications to enforcement agencies in terms of resource allocation and mapping out criminal profiling. Not only do policing agents need to strengthen their enforcement strategies in areas with existing prostitution trends, they would also need to delegate resources towards locations that do not have existing prostitution and to cities that are likely to experience spillover effects.

Fourth, our study builds on top of the findings of Chan and Ghose (2014) by providing a more comprehensive picture of Craigslist's entry effect on other societal outcomes. Chan and Ghose (2014) find that the escort ads on Craigslist have a dampening effect on HIV incidence. The magnitude of this dampening effect, when compared to the HIV-inducing effect from "Personal ads", is relatively small.[30] Through this study, we further found a complementary relationship between erotic ads and casual hookup ads, suggesting that users are likely to use both the nonmarket and prostitution sections simultaneously when seeking sexual acts, which consequently leads to an increase in prostitution counts. Juxtaposing these observations, it is likely that any reductions in HIV incidence through erotic service ads would be nullified by the increase in HIV prevalence, as users who seek prostitution services on Craigslist may also seek casual partners from the nonmarket ads, an act known to increase HIV incidence. The joint consideration of the current findings with that from Chan and Ghose (2014) indicates an unambiguous conclusion --- online platforms that facilitate sexual solicitation bear an overall negative impact on social well-being.

Fifth, our results also make theoretical contributions to the literature of online platforms. While past studies examined whether online platforms affect consumer

[30] From Chan and Ghose (2014), it is seen that a 10% increase in erotic ads is linked with a 0.7% decrease in HIV cases, while the same increase in personal ads leads to a 1.7% increase in HIV incidences, i.e., a ten times increase.

surplus, price dispersion, and competition (e.g., Brynjolfsson et al. 2003, Brynjolfsson and Smith 2000, Brown and Goolsbee 2000), we complement this line of work by investigating a more fundamental relationship involving the impact of online platforms on market participation, in the underexplored context of prostitution. The study finding of a positive relationship between Craigslist entry and prostitution activities enriches our understanding of the nature of online platforms under the context of illegal transactions. The willingness to participate in prostitution via Craigslist, despite the potential risk of legal punishment, is likely encouraged by the perception that these transactions are significantly less risky, as illicit behaviors may be masked by the veil of anonymity in online platforms (Grewal et al. 2004). Moreover, the availability of such services as facilitated by online affordances can lead to the discounting of future costs when satiating immediate needs (Strack and Deutsch 2004). These theoretical explanations are aligned with our empirical findings, and are supported by anecdotal accounts in other contexts, namely the increased sales of drugs and firearms with the increasing use of the dark net.[31]

Moreover, our sub-findings on the growth patterns of Craigslist-enabled prostitution further provide nuanced insights on the impacts of online platforms with regards to its geographical reach. While past studies have found mixed results in terms of whether the effect of platforms extend beyond the local geography of the participants, our study findings revealed that both possibilities are realized in the prostitution market, suggesting that the type of market served by the platform can drastically affect the

[31] Instances of such news reports include https://www.globaldrugsurvey.com/past-findings/the-global-drug-survey-2016-findings/ and http://www.vocativ.com/267755/how-criminals-can-buy-guns-illegally-on-the-dark-net/.

geographical impacts of the online intermediary. Akin to the used vehicle market (Overby and Forman 2015), the gain in utility that accrues from bodily pleasures and monetary payoffs from sexual transactions can reduce the sensitivity towards geographical constraints, motivating participants to travel to neighboring locations that are not directly served by the Craigslist to transact. Similar to the crowdfunding context (Lin and Viswanathan 2016), the prostitution market facilitated by the Craigslist platform enjoys the largest growth in areas that are directly available to both the participants, as the participation costs in these locations are the lowest. Finally, our sub-result shows evidence of the long tail principle at work in our study. To this point, we observe that the growth of Craigslist-enabled prostitution is constituted by a sizeable increase of workers who provide niche sexual services such as S&M and transsexual services, which serves as another validation of long tail effects in online environments.

Our paper is not free from limitations, which leaves potential for future research to expand on our work. First, our study results are limited to showing the relationship between online classified ad sites and prostitution trends. It is possible that other sites or mobile apps, (e.g., Eros.com and Tinder), may facilitate the sexual solicitation differently, leading to a differentiated set of users from that of Craigslist. For instance, it is recently reported that sex workers are using Tinder profiles as a masquerade to solicit clients on the dating app (Dewey 2014). Such approaches may face a set of payoffs and costs that are different from those from Craigslist, resulting in different market outcomes and mechanisms. Second, our study findings are restricted to the U.S. Though similar classified ad sites and solicitation sites operate in other countries, various local factors can affect prostitution incidence differently. For instance, the level of cultural tolerance and legality of prostitution, along with socioeconomic and demographic characteristics of other nations differs from those of the U.S., which can influence entry impacts. Third, it is unclear whether our observed effects will change beyond 2008. In extending our work, future studies may examine whether the closure of Craigslist's solicitation section has an impact on overall prostitution.

Notwithstanding these limitations, our paper represents one of the first works that systematically quantifies the impact of Craigslist's entry on prostitution trends, and have examined the pathways by which the prostitution is impacted by digital platforms. As the use of community-based websites increases, the interplay between platforms and social outcomes warrants greater attention. The unintended use of such sites can result in undesirable criminal acts that undermine legal and judiciary system. There is a need for the law enforcement agencies to keep up with the evolution of online technologies and to adopt new approaches to curb Internet-facilitated crimes. At the same time, site owners should play a more active role to assess and minimize the unintended usage impacts from their site.

Essay 2 – Are Yang and McSteamy More Receptive to a Hot Vote than Meredith and George? Heterogeneity in Treatment Effects in Online Dating

1. Introduction

Recent research has shown that one-third of marriages in the United States begin online (Cacioppo et al. 2013), while almost half of singles went out for date with someone they met online (Canaday and Ross 2017).The number of online dating sites is large and growing, with estimates of around 2500 online dating sites in the US alone[32] and 1400 in the UK[33]. These sites vary in the target audience (e.g. based on sexuality, religion, age), their objectives (e.g. long-term vs. short-term relationships), and, an important aspect related to this study, the features they offer their users.

A key distinguishing feature of online dating versus its traditional counterpart is the ability within dating websites to leave a range of digital signals not replicable in the offline world, which can play an important role in matching outcomes. Given the frictions prevalent in the offline dating world, online dating platforms are introducing new IT-enabled features in order to mitigate the social frictions in the off-line world. Digital platforms are motivated to evaluate such features using experiments given that two-thirds of the features that platforms introduce do not show any significant effect (Kohavi and Thomke 2017). In the context of an online dating platform, in particular, a

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[32] http://www.forbes.com/sites/martinzwilling/2013/03/01/how-many-more-online-dating-sites-do-we-need/

[33] http://www.telegraph.co.uk/women/sex/online-dating/3356126/The-20-most-useful-dating-websites.html

prior randomized experiment with the *anonymous browsing* feature demonstrates that a particular subtle pattern (known as "weak signals") of online communication between women and men is critical in achieving successful matches, particularly for women (Bapna et al., 2016). While that study demonstrates the importance of weak-signaling, which allows regular online profile visits to constitute an important mechanism in dating markets, it offered no recommendations regarding how to push users to actively visit others.

Therefore, our study aims to test the usefulness of one popular feature implemented in dating websites that may encourage user engagement, and more importantly, matching of dates – the *vote-identity revelation*. Online dating platforms typically allow users to "vote" for other users. While information from this feature is used behind-the-scenes by the dating platforms for potential mate recommendations, it is typically not revealed to the users themselves. Our study looks at one aspect of this feature, enabling treated users to observe the *identity* of the user who has (secretly) voted for them by revealing the profile picture icons of voters who liked the treated user and therefore reducing the information asymmetry between users of treated and control groups.[34] Hence, the main focus of this paper is to understand the impact of a *strong-signaling* identity-revelation feature on user engagement and matching outcomes. We suggest that this intervention will increase engagement on the online dating site, and induce users to visit others' profiles more often and ultimately, achieve more matches.

[34] With access to the profile picture icons of the voters, a focal user can further click the profile picture icon and access the voter's online dating profile. Therefore, our treatment allows access to the profile pages of the voters.

Following prior work showing heterogeneous preferences by gender in matching in marriage markets (Hitsch et al. 2010) and online dating platforms (Bapna et al. 2016, Jung et al. 2018), we separate all of our analysis by gender. We ask how the impact of this feature will vary across demographic characteristics including gender, age, ethnicity, and physique type[35] as well as attractiveness. The specific research questions we ask are:

1. How does *vote-identity revelation* feature impact the number of views, messages, and matches that a user sends or receives? How does this effect vary by gender?
2. What are the differential impacts of the vote-identity revelation feature based on difference in users age group, ethnicity, and physique type? How do these effects vary by gender?
3. Separately for both genders, what are the differential impact of *vote-identity revelation* feature based on difference in users own attractiveness levels and users' average voters' attractiveness levels?[36]

To address these questions, we partner with a large North American online dating site that we call *monCherie.com*, to run a randomized field experiment. In this experiment, we follow 100,000 newly registered users, and gift a random sample of 50,000 users a feature that allows treated users to see the identity of voters who rated a treated user with a like. This ability is unique to the online environment as we explain in detail in the following paragraph.

[35] or, body type.

[36] A user's average voters' attractiveness level is the average of attractiveness levels of all voter who sent 'like-votes' to the focal user in the pre-treatment month.

On the dating site we partner with, as well as in many other online dating sites, users can receive and provide attractiveness ratings on a {0, 1}-scale, whereby an user can dislike or like another user. The default setting is that the identity of raters is kept secret, in that they are not visible or known to the focal user who receives attractiveness ratings. The focal user can receive messages from the site indicating that "X" *number* of users have rated them with a like, but these messages do not contain the *identity* of the users who have rated them with a like.[37] However, in matching markets such as online dating, the raters' identity information serves as a key ingredient for the background recommendation and matching engine of the site. Thus, the default setting in online dating resembles that of the offline dating market, in that there exists information asymmetry about people's preferences for each other. Specifically, even though a focal user (ratee) may have been rated with a like by another user (rater), she would not be aware of the identity of the particular user who rated her with a like. This creates information asymmetry in that the rater holds information that the ratee does not have access to. The *vote-identity revelation* feature breaks down this information asymmetry by informing the ratee of the identity of the rater if the rater has given her "thumbs up" for attractiveness.

Theories prevalent in the computer mediated communication (CMC) literature and information processing literature, suggest that the impact of the *vote-identity revelation* feature on users' communication related outcomes could be diverse. According to the media richness theory, using CMC can provide a limited bandwidth to

[37] On the contrary, if the focal user receives a dislike-vote that information is never revealed to that user.

convey social cues due to its leaner interface, and this makes the platform less useful for tasks related to negotiating social relations. Yet with multiplicity of cues, like adding the *vote-identity revelation* feature, we can expect better users' performance in CMC for an equivocal task like searching and communicating with a potential date (Dennis and Kinney 1998). In addition, the social information processing theory (SIPT) suggests that users can expect a better relationship outcome in CMC with passage of enough time and exchange of enough messages, when engaged in utilizing the communication cues available in the online environment (Walther 1992 and 1995). Further, Walther (1996) proposed that CMC have the potential to become "hyperpersonal," whereby a heightened level of fondness and intimacy is possible in computer-mediated mediums for communication. Later, empirical research that uses SIPT under online dating context shows that Walther's theory also explains user intimacy and impression formation for online dating users (Ellison et al. 2006, Gibbs et al. 2006, Farrer et al. 2009).

When looking for the impact of identity-descriptive communication cues, evidence from research in online communities shows that community members find these cues helpful when evaluating online reviews, and experience positive impression formation while rating the reviews with identity-descriptive cues (Forman et al. 2008). Similarly, in our online dating context, the *vote-identity revelation* feature contain identity-descriptive information that can powerfully influence dating website users' engagement and matching responses within the site. Therefore, with support from extant literature in CMC and information processing, we expect that our *strong-signaling* intervention in the online dating context will lead to more engagement and matching outcomes among users of the dating website.

Our results show that, indeed, both female and male treated users experience a boost in engagement with the online dating site. That is, not only do we causally show that the communication of a treated user increases, but the overall likelihood of initiating communication increases for women who have the *vote-identity revelation* feature. We find that there is 12.59% overall increase in matches for the participants in the dating markets, whereas there is 17.69% increase in matches for treated women. This is particularly important given that women have been shown to adhere to social norms that dictate that they are less likely to initiate communication or make the first move (Bapna et al. 2016). The *vote-identity revelation* feature seems to trigger women to overcome inhibitions and initiate interactions. This demonstrates how technology-enabled features such as information-revelation about the identity of a user who has liked the focal user, can improve the efficacy of an age-old social process linked to human happiness, such as finding a date.

Further, our results indicate that there is heterogeneity in treatment effects across age, ethnicity, and body type dimensions whereby different user cohorts have different reaction to the treatment. We also find heterogeneity in treatment effects based on the treated user's own attractiveness levels, user's average voters' attractiveness levels, and the interaction of the treatment with user's own attractiveness scores and average voters' attractiveness scores. Our results show that for male users, we identify a positive "ego effect" for those who have high own attractiveness scores since their self-initiated matches increases while viewing and messaging other females decreases. It can be argued that the *vote-identity revelation* feature makes highly attractive male users confident and selective, by achieving better matching outcomes while reducing their engagement outcomes. On the other hand, when receiving votes from a pool of highly attractive voters, we find that females experience an "encouragement effect," and their overall self-initiated engagement and matching outcomes in the dating website increases. Finally, we used a three-way interaction among the *vote-identity revelation* treatment, user's own attractiveness score, and user's average voter's attractiveness score, and found a dampening effect on all online dating activity levels (like viewing, messaging, and matching) that was present for both genders.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 describes the institutional details of monCherie.com, the online dating site that we partner with to conduct our randomized experiment. Section 4 explains the setup of the randomized experiment as well as some empirical regularities. Section 5 describes our results. Finally, in Section 6 we conclude and provide a discussion of our findings.

2. Literature

Our study is at the intersection of literatures related to dating markets, marriage markets, and online ratings. A key finding in the literature on dating and marriage markets is the gender asymmetry in preferences and actions (Fisman et al. 2006, Hitsch et al. 2010) and, relatedly, the social frictions that exist in these markets (Piskorski 2012, Bapna et al. 2016). Prior research has demonstrated that women and men have asymmetric preferences for characteristics of a potential partner: women place a higher importance on intelligence (Fisman et al. 2006), income and education (Hitsch et al. 2010), while men value appearance (Fisman et al. 2006).

Another source of gender asymmetry in dating and marriage markets comes from social frictions. These social frictions are often a result of high search costs due to, for example, geographical constraints and incomplete information about a potential partner, but also come from existing social norms. While many search frictions are reduced in the online context, the social frictions stemming from asymmetric social norms still exist. In particular, the age-old social norms that inhibit women from making the first move are still evident in online dating markets (Piskorski 2012, Bapna et al. 2016).

Dating markets uphold other sources of asymmetries along demographic dimensions. Extant research has shown that dating preferences and actions differ along the dimensions of age groups, ethnicity and body types. When looking at gender and age groups differences, it is reported in relationship sciences literature that men seek younger women, while women seek older men (Bolig et al., 1984). Further, studies showing differences in dating attitudes between younger and older women reported that, with increase in age, older women systematically seek men closer to their own age, or even seek younger men (Harrison and Saeed 1977, Jagger 2005). For men, with increase in age, older men preferred increasingly younger females (Alterovitz et al. 2011). Literature on racial impacts on dating shows that at the time of initiating communication, African Americans and Hispanics are less interested in the erotic or sexual aspect of dating than their White counter parts (Glenn and Marquardt, 2001). As a result, hookups[38] were not popular among African American and Latino groups during initial dating encounters (Williams 1998). Further, studies have shown that females across all races show same-

[38] "Hooking up" could mean anything from kissing to intercourse during the first offline meeting of potential mates.

race preferences, whereas men are open to inter-racial dates (Fisman et al. 2008, Hitsch et al. 2006, Yancey 2009). In relation to the literature on body types and dating, Glasser et al. (2009) reported African American and Hispanic men prefer heavy bodied or curvy females, while White males tend to like thin and toned female physical appearances.

Prior work has also shown that individual attractiveness also plays a crucial role in shaping relationships, but the direction of its effect at influencing relationships is ambiguous in extant literature. On one hand, attractive people fare better in life outcomes than unattractive people according to previous studies (Eagly et al., 1991; Langlois et al., 2000). Research in social psychology has linked attractiveness with confidence under social judgement situations and performance in the job market context (Mobius and Rosenblat 2006). Further, in dating studies, assortative matching on the dimension of attractiveness has been the trend reported, which suggests that users match along similar levels of attractiveness (Hitsch et al. 2010). On the other hand, individuals who are highly attractive, will likely have access to more and better alternatives. This makes them pricey and feel less dependent on new sources of relationships (Thibaut and Kelley 1959, Lewin et al. 1944). When taken to an extreme, individuals are subject to negative implicit evaluations based on their attractiveness levels (Maner et al., 2009). Such negative evaluations have implication for interpersonal derogation (Agthe & Sporrle, 2009; Forsterling et al., 2007) and social avoidance (Agthe et al., 2008). Finally, the role of attractiveness in mating literature have revealed that attractiveness matters when seeking romantic-partners albeit often asymmetrically across genders (Eastwick and Finkel 2008; Reis et al. 2013).

Finally, our work relates with the online ratings literature. Prior work has demonstrated the importance of technology enabled signaling mechanisms to tackle social inhibitions in dating markets, an example is non-anonymous browsing of profiles (Bapna et al. 2016). Online rating systems are another mechanism of signaling used in many other online markets such as eBay, Amazon, iTunes, Spotify, Netflix, and others. Research on online rating systems has indicated the positive impact that positive product ratings have on sales of books (Chevalier and Mayzlin 2006), movies (Liu 2006, Dellarocas et al. 2007), and music (Dewan and Ramaprasad 2012) and the importance of such ratings for buyers and sellers on eBay (Standifird 2001, Resnick and Zeckhauser 2002). In addition, research on book ratings on Amazon has indicated that identity disclosure of the reviewer along with a positive rating is associated with an increase in product sales (Forman et al. 2008).

It is important to note that online rating system used in the context of online dating is different from the online rating systems on traditional product platforms. While online ratings on product platforms are visible to users and help in making purchase decisions, these ratings are not visible on online dating profiles to other users. That is, while it is clear on the Amazon.com product page that users, on average, rated a book with four stars out of five, these average ratings are not visible on online dating profile pages for a visiting user. In actuality, users can see their own ratings in their profile pages, but not that of others.[39] Thus, the signal of quality or, in the dating context, of interest is explicit only to the focal user who interprets self-only ratings as his or her

[39] Note that we interpret a user's online rating as the total count of 'like-votes' that is visible to that user in his or her profile page.

quality in the online dating website. Besides this, the use of the ratings in online dating websites are also as a source of information that the site uses on the back-end to feed into its recommendation engine and suggest potential mates to users.

Our study contributes to the existing literature on dating markets and online ratings. Accordingly, it aims to fill the gap between the online dating and online ratings research streams. We examine the main treatment effects for the *vote-identity* revelation feature on treated users engagement and matching outcome in the dating website. We also look at heterogeneity in treatment effects along demographic dimensions, like gender, age group, ethnicity, and body type. Finally, we study the role of attractiveness of focal users and voting users in moderating the effects of the *vote-identity* revelation feature. In the next section we discuss the institutional details of our partner online dating website, where we conducted the randomized field experiment.

3. Institutional Details

To conduct the experiment, we partnered with one of the largest online dating websites in North America, which we call monCherie.com (name disguised). MonCherie.com constitutes a regular online dating website and offers the following features to its users, which are typical of most other online dating websites:

- Users may set up their own well-structured online profiles where they describe themselves as well as reveal characteristics sought in a desired partner. Users may also include a set of their photos in their viewable profiles.
- Users may view profiles of all other users without limitations.
- Users may search for profiles of other users using an advanced search engine that allows filtering by age, location, religion, and a large number of other demographic

variables. Users may also discover partners using a proprietary recommendation engine that is provided by the website.

- Users may send private messages to any other user.
- Users may like-vote other users when they visit their profile pages; In the online dating website's proprietary recommendation engine that allows users to discover partners by showing them profiles of potential matches, users can like or dislike other users.[40]

In addition to these features, monCherie.com constitutes a typical *freemium* community: most of the users sign up for a free account ("free users"), which allows them to utilize all the key features listed above. In addition to these free features, users can obtain a premium subscription if they pay approximately $1 per month (exact value changed for de-identification purposes). The premium subscription consists of a fixed bundle of premium features that include, among other incremental features, the ability to anonymously browse profiles of other users (Bapna et al. 2016) and the feature we study here, *vote-identity revelation*, the ability to view the identity of the users who have given a focal user a like.

4. Experiment, Data, and Empirical Regularities

Our experiment was conducted on 100,000 new users of monCherie.com, the online dating partner website, over three consecutive months, referred as Month 1 (Pre-treatment), Month 2 (During treatment) and Month 3 (Post-treatment) in year 2016. A randomly selected treatment group of 50,000 users was treated with a gift of one month

[40] In the mobile phone version of the website, users can swipe right to like other users, and swipe left otherwise.

of the *vote-identity revelation* feature during Month 2, while the remaining users stayed with the default settings and served as our control group. Figure 3 shows the *vote-identity revelation* experiment diagrammatically.

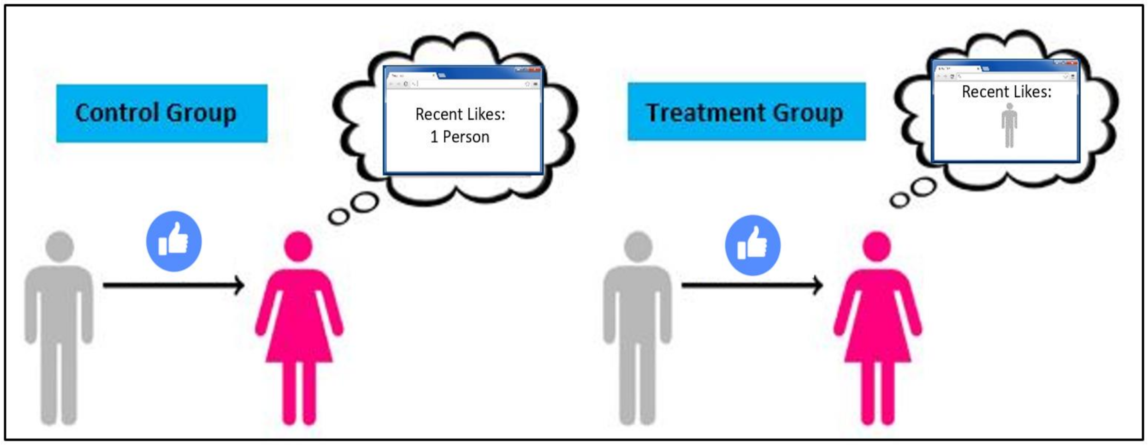

Figure 3 - Vote-identity revelation experiment

Our *vote-identity revelation* treatment was randomly assigned that makes it a strictly exogenous instrument. Therefore, using this randomized controlled trial set up we can causally identify the treatments effects. As a result, our study is free from endogeneity concerns, and other non-random differences that can partially explain our observed difference in treated and control groups, which if present could confound the analysis. Further, the treatment was implemented automatically by the website, whereby the treated users received the treatment as a gift, without any required actions on their side, and we do not ask for anything in exchange from these users. Further, users are unaware of being a part of the experiment, so observer bias is not applicable.[41]

[41] Treated users are not aware of the fact that the *vote-identity revelation* treatment is part of an experiment. They acknowledge the feature as a gift from the website.

We collected our data using random sampling, whereby we got data for 100,000 random users who are part of the experiment, as well as other users who directly interacted with the focal users in experiment. We term the users with whom our focal users interacted as the first-degree other users group. We further have data from another set of users who interacted with the first-degree other users, can call them the second-degree other users group. For each of the 100,000 users in our experiment, we have time-stamped viewing, messaging, and critically for this study, we have time-stamped votes (i.e. like-vote is 1, dislike-vote is 0), both sent and received by these users. Further, our dataset consists of data from approximately five million first-degree other users of the website, who interacted with the focal users through the engagement channels, like viewing, messaging, or voting. We also have viewing, messaging, and voting information for the second-degree other user's group.

In addition, we have data on a set of demographic variables such as gender (female or male), age[42], sexual orientation (straight, gay, or bisexuals), ethnicity (asian, black, white, or mixed race), and body types (average, curvy, fit, or full figured). We are also able to determine whether the users are valid (valid = 0 represents an invalid user, if the user is a spammer or a bot as determined by internal algorithms at monCherie.com). In this study we limit our sample only to users who are straight and valid prior to the manipulation.

For this study, we generate two synthetic demographic variables related to attractiveness – user's own attractiveness score, and user's average voters' attractiveness

[42] Age is classified into age groups 18 to 24, 25 to 29, 30 to 39, 40 to 49, and 50 and above.

score. The focal user's own attractiveness is measured by the *own attractiveness score* variable, which is the total count of like votes divided by the total count of votes. Mathematically,

$$Own\ Attractiveness\ Score_i = \frac{\sum_{j \in J} Like\ Vote_{j \to i}}{\sum_{j \in J} Like\ Vote_{j \to i} + \sum_{j' \in J'} Dislike\ Vote_{j' \to i}}$$

where, i is a focal user, $j \in J$ is a voter j who belongs to a set of voters J that gave user i a like-vote, and $j' \in J'$ is a voter j' who belongs to a set of voters J' that gave user i a dislike-vote.

The measure user's average voters' attractiveness score captures the average attractiveness of the voters who like a focal user. Mathematically it can be represented as,

$$Average\ Voters'\ Attractiveness\ Score_i = \frac{\sum_{j \in J} Own\ Attractiveness\ Score_j}{J}$$

where, i is the focal user, $j \in J$ is a voter j who belongs to a set of voters J that gave user i a like-vote, and Own Attractiveness $Score_j$ is the own attractiveness score measure for user j.

Table 10 compares the treatment and control groups separately for both genders for a few selected variables (age, white, and own attractiveness score) in the time period prior to manipulation.[43] It can be seen from Table 10, the treatment and control groups are statistically indistinguishable from each other prior to manipulation. It is also interesting to note that the own attractiveness scores for males is significantly lower than

[43] Pre-treatment comparison results for the entire list of variables is available from authors upon request.

for females - approximately 0.17 for women compared to 0.08 for men (on a 0-to-1 scale). In contrast to ratings in other matching markets such as eBay, there is no evidence of a leniency effect (Resnick and Zeckhauser 2002) in user ratings in online dating markets.

Table 10. Pre-Treatment Comparison of Treatment and Control Groups

Gender	Manipulation	Variable	Mean	Std Err	t-value	p-value
Female	Control	Age	30.844	0.242	-0.54	0.587
Female	Treated	Age	30.986	0.099		
Female	Control	White	0.520	0.012	-1.62	0.104
Female	Treated	White	0.541	0.005		
Female	Control	Own Attractiveness Score	0.174	0.005	-0.99	0.322
Female	Treated	Own Attractiveness Score	0.181	0.005		
Male	Control	Age	29.329	0.169	1.62	0.1061
Male	Treated	Age	29.232	0.068		
Male	Control	White	0.502	0.009	-0.68	0.4978
Male	Treated	White	0.509	0.004		
Male	Control	Own Attractiveness Score	0.080	0.001	1.277	0.2018
Male	Treated	Own Attractiveness Score	0.079	0.001		

In defining our outcome of interest, we use online dating variables like views and messages, and rely on prior work on online dating that has defined a "match" as the exchange of at least four messages[44] between two parties (please see Bapna et al. 2016 for a detailed description).[45] Using this definition, we examine the impact of *vote-identity*

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[44] Note that four messages are a lower threshold. Many observed exchange of messages are much longer than four messages.

[45] Prior research (Hitsch et al. 2010, Bapna et al. 2016) and anecdotal evidence from online dating industry has pointed out that exchange of three messages between potential couples is a good predictor of match, when participants exchange phone numbers or ask their potential mate out for date during an online dating message exchange session. Accordingly, in this paper we conservatively choose exchange of four messages as definition of match.

revelation treatment on the number of views, messages, and matches that are both sent and received by the focal users. In this study, matches sent are those where the focal user initiates the exchange of the four messages, and matches received are those where the focal user is the recipient of the first message in the four message exchange. Collectively, we term these outcome variables as online dating engagement (i.e. view sent, view received, message sent, and message received), and matching (i.e. matches sent and matches received) variables. Overall, they are the *online dating activity* variables. We standardize the independent variables to run interpretable econometric models. Table 11 reports the descriptive statistics of our data separately for both genders.

Table 11: Summary Statistics From the Vote-Identity Revelation Experiment

Variables	Obs.	Mean	Std. Dev.	Min	Max
Females					
Vote-identity revelation Treatment	3858	0.504	0.5	0	1
Own Attractive Score	3358	0.282	0.157	0	1
Own Attractive Score (Standardized)	3358	0	1	-1.799	4.586
Average Voters' Attractiveness Score	3305	0.067	0.036	0	0.8
Average Voters' Attractiveness Score (Standardized)	3305	0	1	-1.878	20.473
View Sent	3858	31.612	77.947	0	1515
View Received	3858	94.454	147.518	0	3028
Message Sent	3858	6.789	15.06	0	235
Message Received	3858	23.174	43.173	0	1342
Match Sent	3858	0.631	2.205	0	39
Match Received	3858	3.043	7.127	0	129
Males					
Vote-identity revelation Treatment	8675	0.496	0.5	0	1
Own Attractive Score	7829	0.106	0.098	0	1
Own Attractive Score (Standardized)	7829	0	1	-1.078	9.138
Average Voters' Attractiveness Score	7082	0.301	0.138	0	1
Average Voters' Attractiveness Score (Standardized)	7082	0	1	-2.181	5.055
View Sent	8675	57.747	147.228	0	2641
View Received	8675	16.94	36.438	0	809
Message Sent	8675	14.21	49.748	0	1116
Message Received	8675	4.23	11.493	0	204
Match Sent	8675	1.689	6.313	0	151
Match Received	8675	0.314	1.035	0	25

In order to identify the treatment effects in our study, we start with statistical t-test modeling, given that our treatment is exogenously administered using a randomized field experiment. Further, utilizing the count data nature of our dependent variables, we employ a Poisson econometric model to identify the heterogeneity in treatment effects. In particular, we estimate regressions of the following form:

(1) Regression for HTE in User Demographics: In this regression, an online dating activity dependent variable is regressed on treatment, along with treatments interaction with age group dummies, ethnicity dummies, and body type dummies that represents heterogeneity in treatment effects along user demographics.

$$\begin{aligned} Online\ Dating\ Activity_i &= \rho_T \times Treatment_i \ + \\ &\quad \alpha_I \times Age\ Group_i + \ \alpha_T \times Treatment_i \times Age\ Group_i + \\ &\quad \beta_I \times Ethnicity_i + \ \beta_T \times Treatment_i \times Ethnicity_i + \\ &\quad \gamma_I \times Body\ Type_i + \ \gamma_T \times Treatment_i \times Body\ Type_i + \varepsilon_i \qquad (1) \end{aligned}$$

where *i* indicates the focal user, who can either be in the treatment group or control group; $Online\ Dating\ Activity_i$ is a representative outcome variable that can specifically be views, messages, or matches, both sent or received; $Treatment_i$ is the binary indicator for the *vote-identity revelation* treatment, which equals to 1 if the user is in the treatment group, and equals zero otherwise; coefficient α_I, β_I and γ_I captures the independent impact of focal user's age group dummies, ethnicity dummies, and body type dummies, respectively; coefficients ρ_T captures the average treatment effect (ATE); coefficients α_T, β_T and γ_T captures the heterogeneous treatment effect (HTE) for focal user's age group, ethnicity, and body type demographics, respectively; and ε_i is the error term.

(2) Regression for HTE in User Attractiveness: In this regression, an online dating activity dependent variable is regressed on treatment, control variables, along with

treatments interaction with users' own attractiveness score, users' average voters' attractiveness score, and both such that it represents heterogeneity in treatment effects along users attractiveness dimensions.

$$
\begin{aligned}
&\mathit{Online\ Dating\ Activity}_i = \\
&\quad \rho_T \times \mathit{Treatment}_i \ + \\
&\quad \alpha_I \times \mathit{Own\ Attract}_i + \alpha_T \times \mathit{Treatment}_i \times \mathit{Own\ Attract}_i + \\
&\quad \beta_I \times \mathit{Ave\ Voters'\ Attract}_i + \ \beta_T \times \mathit{Treatment}_i \times \mathit{Ave\ Voters'\ Attract}_i + \\
&\quad\quad \gamma_T \ \times \mathit{Treatment}_i \times \mathit{Own\ Attract}_i \times \mathit{Ave\ Voters'\ Attract}_i + \\
&\quad\quad \mu_I \times \boldsymbol{Controls}_i + \ \varepsilon_i
\end{aligned} \tag{2}
$$

where *i* indicates the focal user, who can either be in the treatment group or control group; $\mathit{Online\ Dating\ Activity}_i$ is a representative outcome variable that can specifically be views, messages, or matches, both sent or received; $\mathit{Treatment}_i$ is the binary indicator for the *vote-identity revelation* treatment, which equals to 1 if the user is in the treatment group, and equals zero otherwise; coefficient ρ_T captures the average treatment effect (ATE), holding constant any individual heterogeneity; coefficients α_I and β_I captures the independent impact of focal users' own attractiveness levels and users' average voters' attractiveness levels, respectively; coefficient α_T captures the ego effect, due to treatments interaction with users' own attractiveness levels; whereas, coefficient β_T captures the encouragement effect, due to treatments interaction with users' average voters' attractiveness levels; the coefficient γ_T captures the three-way interaction among treatment, users' own attractiveness, and users' average voter's attractiveness; finally, $\boldsymbol{Controls}_i$ is a vector of focal user-specific dummy control variables representing user age cohorts, ethnicities, and body types; and e_i is the error term.

5. Experimental Results

5.1 Main Treatment Effects

The key differences in users' engagement and matching outcomes in response to the treatment are presented in Table A8 (in Appendix 1). Our results show 12.59% overall increase in matches for users of the dating website, where, the female cohort largely drives the overall increase in matches with 17.69% increase (Table A8). In order to achieve ease of interpretability, we represent the t-test results using Figure 4. The figure showcases the ±2 standard error bars from the mean for the online dating activity variables (i.e. views, messages, and matches, both sent and received) corresponding to the treatment and control groups (i.e. manipulation = 0 is the control group, and manipulation = 1 is the treatment group). We highlight all cases with significant differences at the 99% level of significance between the treated and control groups with black boxes.[46] Our results show that females experience a significant increase in self-initiated views and messages under the influence of the treatment. These key engagement metrics are most valuable to the online dating website management as well as female website users, given that it is common knowledge that females initiate very low counts of engagement outcomes in dating websites. We interpret these results as a boost in female confidence due to exposure to the *vote-identity revelation* treatment, whereby their views sent increased by 16.6% and messages sent increased by 12.4%. Further, we find that

[46] Thus, our black boxes represent cases were the difference in sample means between treatment and control groups has p-value ≤ 0.01

matches received by females also increased to the order of 17.3%, which suggests that increase in engagement is complemented with increase in matches as well for the female cohort.[47] With regards to males, we found increase in matches received at 95% significance level but the match received percentage gain is higher for females.

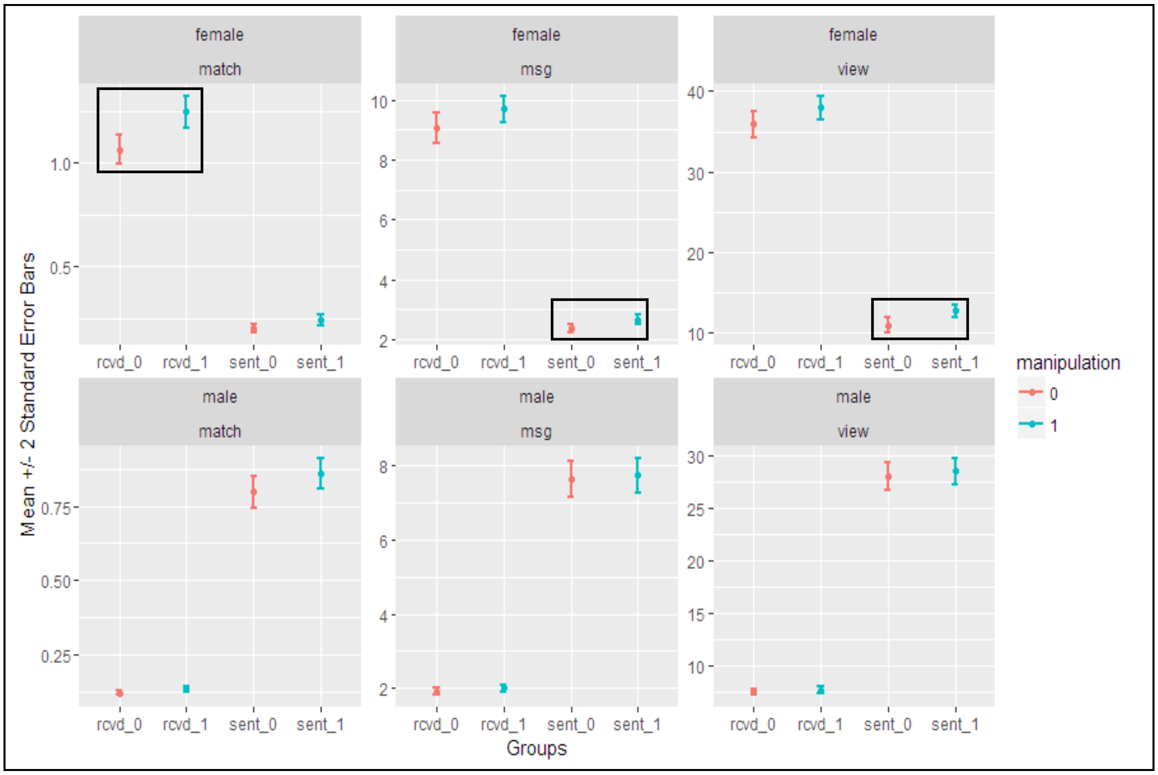

Figure 4: Standard error bars showing main treatment effects

Note. The black box represents cases with significant differences between treatment and control groups at p-value ≤ 0.01. Terms rcvd_0 is control group's received variable, rcvd_1 is received variable in treatment group, sent_0 is control groups sent variable, and sent_1 is treatment group sent variable. Term msg represent messages.

[47] In Figure 4, note that females views, messages and matches received are larger in numbers than views, messages and matches sent by them. For males, it's the opposite scenario, which showcases the gender asymmetries prevalent in online dating markets.

5.2 Heterogeneity in Treatment Effects (HTE)

Next, we explore heterogeneity in treatment effects (HTE) along the following demographic dimensions - age group, ethnicity, and physique type. The results along the age groups dimension are reported in Figure 5.[48] We didn't find any difference between sample means of treated and control groups at 99% level of significance, but at 95% level of significance (highlighted with dashed black boxes in Figure 5), our results show that for females in the '18 to 24' age group, there is significant increase in match received to the tune of 55.6%. But more interestingly, females in their forties (i.e. the '40 to 49' age group) show a very high 72.7% increase in self-initiated matches, which shows that women take the first move. Therefore, two different cohort of female users separated at least by fifteen years in age, show significant uptake in their match related outcome variables. This suggests that our *vote-identity revelation* treatment impacts a broader spread of women who are substantially dispersed along the age dimension. When looking at men, we didn't find any significant difference in the treatment effect along their different age groups.

[48] Table A9 reports the actual t-test results.

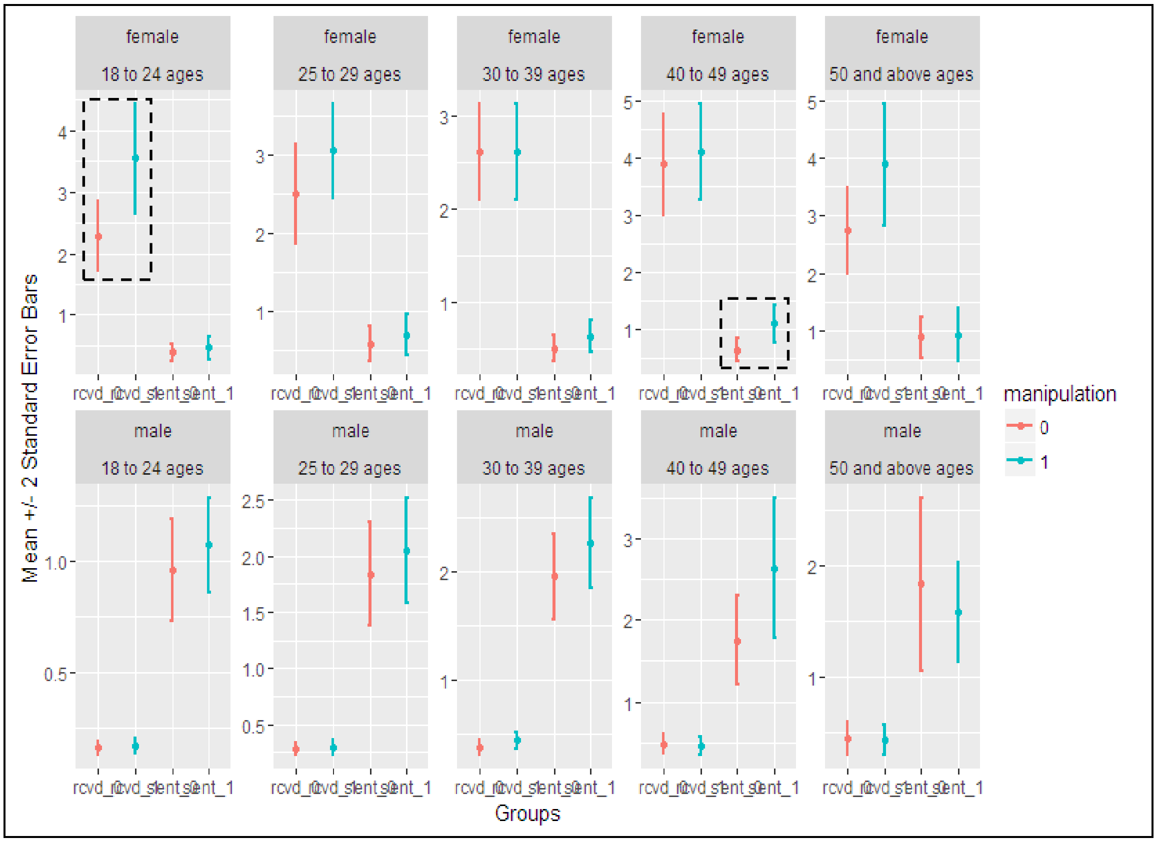

Figure 5: Heterogeneous treatment effects for different age groups.

Note. The dashed-black box represents cases with significant differences between treatment and control groups at p-value ≤ 0.05. We report matches sent and matches received as outcome variables in the figure. Terms rcvd_0 is control groups received variable, rcvd_1 is received variable in treatment group, sent_0 is control groups sent variable, and sent_1 is treatment group sent variable.

In Figure 6 we report HTE results for ethnicities White, Black, Asian and mixed races.[49] At 99% level of significance, our results show significant treatment effects for Asian females. Due to the treatment, Asian females significantly increase their self-initiated matches by a very large 161.4% (reported in Table A10). This result is interesting given that in extant studies Asian females are reported as "hyperfeminine," accordingly they show traits like passivity, weakness, quietness, and a sense of duty (Espiritu 1997; Tajima 1989; Pyke and Johnson 2003). Therefore, our results show a

[49] Table A10 reports the t-test results for different ethnicities.

counterintuitive scenario, whereby the Asian females experience a boost in confidence due to the *vote-identity revelation* treatment. Further, studies have shown that western men are fascinated by Asian women, whereby they perceive Asian women as sexually exotic. This trend is colloquially known as 'Asian fetish,' or 'yellow fever' (Prasso 2005), which can also account for the increase in matches that we see in our results. Accordingly, our results suggest the possibility that Asian females initiate matches with White men.

For females who reported mixed race[50] as ethnicity in their dating profile pages, we find a significant increase in inbound matches for the treatment group. These users of mixed ethnic background show a very high 127.6% increase in match received at 99% level of significance. With regards to White and African American females, our study didn't find any significant treatment effect on match related outcome variables. Further, we didn't find any significant treatment effect for the male user base along the race dimension at the 99% level of significance.

[50] We define individuals as mixed race when they report themselves with two ethnicities in the dating website.

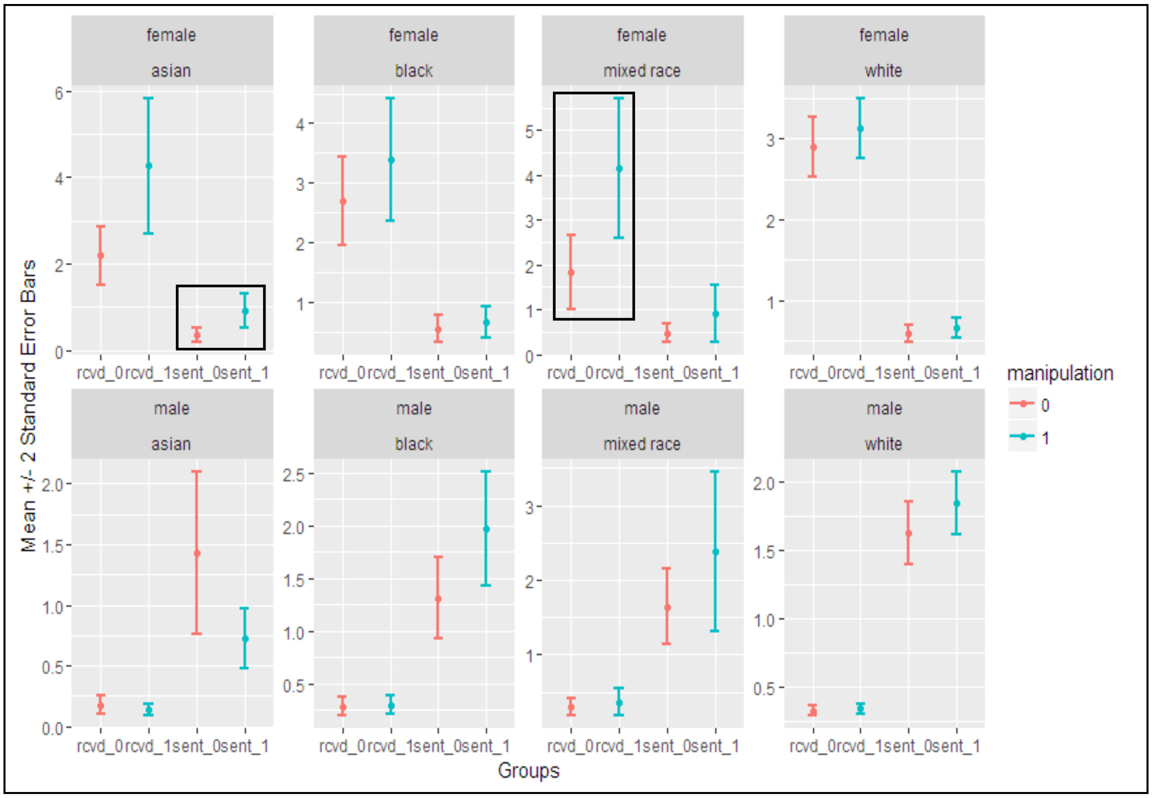

Figure 6: Heterogeneous treatment effects for different ethnicities.

Note. The black box represents cases with significant differences between treatment and control groups at p-value ≤ 0.01 We report matches sent and matches received as outcome variables in the figure. Terms rcvd_0 is control groups received variable, rcvd_1 is received variable in treatment group, sent_0 is control groups sent variable, and sent_1 is treatment group sent variable.

Finally, we look for HTE in physique types as another dimension of heterogeneity. We consider *average*, *fit*, *curvy*, and *full-figured* as the four body types cohorts. Our results in Figure 7 show significant treatment effects for females who reported themselves as of *curvy* body type. We find that *curvy* female show significant increase in matches received to the tune of 42.9% (reported in Table A11) at 99% level of significance. We further look at curvy females online dating engagement outcome, by checking their viewing and messaging behavior, and find that only in their views sent there is significant increase at the 99% level of significance (reported in Table A12). Therefore, we can infer that increase in matches received for *curvy* females is predominantly driven by outbound profile viewing. *Curvy* females can leave a 'weak signal' each time they view a potential mates profile, and this induces men to initiate the first message (Bapna et al. 2016). As a result *curvy* females experience increase in inbound matches.

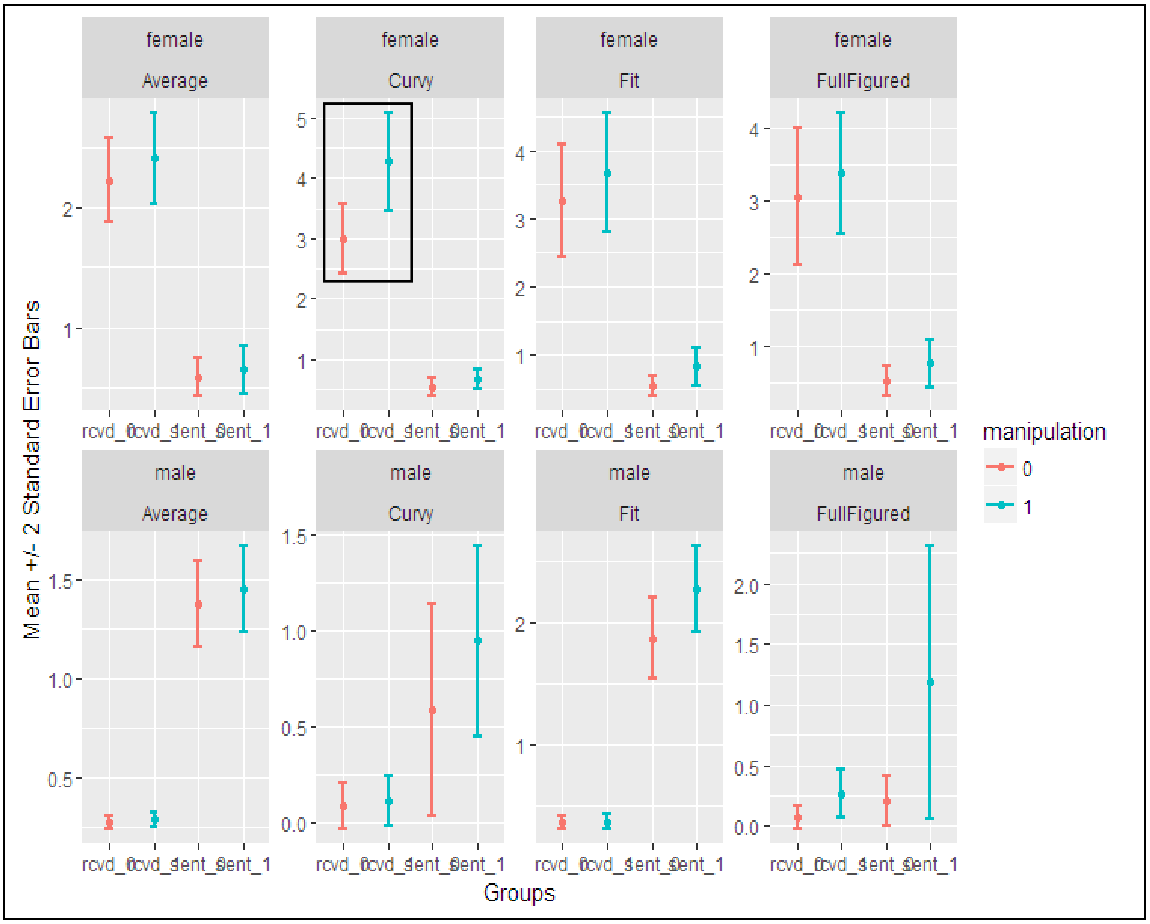

Figure 7: Heterogeneous treatment effects for different body types.

Note. ▭ The black box represents cases with significant differences between treatment and control groups at p-value ≤ 0.01. We report matches sent and matches received as outcome variables in the figure. Terms rcvd_0 is control groups received variable, rcvd_1 is received variable in treatment group, sent_0 is control groups sent variable, and sent_1 is treatment group sent variable.

We further look at the heterogeneity in treatment effect (HTE) results by combining all age group, ethnicity, and race dimensions using a Poisson regression model. Our results are reported in Table 12. Along the age group dimension, similar to the statistical t-test results, we find that matches initiated by females in their forties (i.e. the ‘40 to 49’ age group) significantly increased by 53.42% due to the treatment[51] (see in Model 1 with coefficient value 0.428).[52] On the contrary, in Model 2 we find that matches received for females in their forties significantly dropped by 31.2%. Therefore, our results suggest that the *vote-identity revelation* feature influenced females in their forties to initiate more matches at the cost of receiving less matches. Providing females with a push so that they can initiate more matches by themselves was a core reason to study our *strong signaling* feature. For females in their late twenties (‘25 to 29’ age group) and thirties (‘30 to 39’ age group), our treatment effects show a fall in their matches received to the tune of 24.8% and 36.8% decrease, respectively. For the male users, we find consistent increase in self-initiated matches due to the treatment ranging from 28% to 67% increase for all their age group cohorts. Interestingly, we find that men from older age groups showed higher percentage increase in their matches sent (in Model 3).

When looking at heterogeneous treatment effects along users’ race dimension, our results show that both self-initiated matches and matches received significantly increased by 135.14% and 83.86%, respectively, for Asian female users which supports our statistical t-test results. A similar increase in both type of matches due to the treatment is seen for mixed race female users, who reported themselves with two ethnic groups in our

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[51] Note that this result is at 99% level of significance.

[52] Since we are using Poisson regressions, we report the coefficients in Table 12 in percentage term using $(e^{\alpha} - 1) * 100$, where e is the exponential constant and α is the regression coefficient.

data set. Finally, for African American females we find that there is only increase in their inbound matches by 14.34% magnitude (reported in Model 2 with regression coefficient 0.134). While looking at males, we find a unique result where Asian men have a negative and significant coefficient for their self-initiated matches, accordingly their matches sent decreased by 55.07%. This is interesting given that for other ethnic groups (African American and mixed race) our feature shows significant increase in outbound matches for males.

Similar to the statistical t-test results, our regression results for curvy females show an uptake in matches received. We find that females with curvy physique type show 23.12% increase in their received matches (in Model 2). Further, we find treatment effects showing decrease in self-initiated matches for females reporting “average” as body type. Interestingly, men of all reported body types averages around 75% decrease in their self-initiated matches. In our regressions, we didn’t find significant impacts on matches received (Model 4) for men at least at 95% level of significance for all the demographic dimensions – age groups, ethnicities, and body types.[53]

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[53] For detailed results on HTE along users’ engagement and matching outcomes, like views, messages, and matches both sent and received please check Appendix Tables A13 (for females) and A14 (for males).

Table 12: Heterogeneous Treatment Effects Along Demographic Dimensions

	Females		Males	
	Match Sent	**Match Rcvd**	**Match Sent**	**Match Rcvd**
	Model 1	**Model 2**	**Model 3**	**Model 4**
Treatment	0.223***	0.173***	0.103***	0.048
	(0.04)	(0.02)	(0.02)	(0.04)
Treatment interactions with				
Age groups -				
18 to 24 ages	-0.022	-0.104	0.250***	0.103
	(0.14)	(0.07)	(0.07)	(0.14)
25 to 29 ages	-0.012	-0.285***	0.247***	0.084
	(0.14)	(0.07)	(0.06)	(0.14)
30 to 39 ages	0.069	-0.459***	0.298***	0.238*
	(0.13)	(0.07)	(0.06)	(0.13)
40 to 49 ages	0.428***	-0.374***	0.512***	-0.034
	(0.14)	(0.07)	(0.07)	(0.14)
Ethnicities -				
Asian	0.855***	0.609***	-0.800***	-0.330*
	(0.15)	(0.06)	(0.08)	(0.19)
Black	0.041	0.134**	0.244***	-0.032
	(0.13)	(0.06)	(0.06)	(0.13)
Mixed Race	0.528***	0.696***	0.193***	0.093
	(0.17)	(0.08)	(0.06)	(0.15)
Body types -				
Average	-0.390***	-0.069	-1.657***	-1.262
	(0.15)	(0.07)	(0.44)	(0.78)
Curvy	-0.204	0.208***	-1.210**	-1.031
	(0.15)	(0.07)	(0.52)	(1.09)
Fit	-0.066	-0.024	-1.537***	-1.293*
	(0.16)	(0.07)	(0.44)	(0.78)
Observations	3858	3858	8675	8675

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Role of Attractiveness

Table 13A and 13B presents results from our empirical analysis related to attractiveness separately for females and males, respectively. The examination of the coefficients of the interaction terms with our *vote-identity revelation* treatment reveals the heterogeneity in treatment effects (HTE) along the attractiveness dimension. At first, we look for HTE along users' own attractiveness levels. Interestingly, for the female cohort we didn't find any significant effect on users matching outcomes when own attractiveness is interacted with the treatment. Yet for males, we find a significant increase in matches sent. Accordingly, a unit increase is treated males' own attractiveness will increase their outbound matches by 3.36% (see Table 13B Model 1). This is counter intuitive given that with increase in own attractiveness, male users now showcase more confidence to actively reach out to their potential mates, whereas female users do not depend on their own attractiveness as a deciding factor under exposure to the treatment. Further, our results show an evidence for a positive "ego effect," whereby treated male users decrease their self-initiated views and messages (see Table A16) while experiencing increase in matches sent, because of their own attractiveness.

Next, we analyze the effects for the independent variable that interacts *vote-identity revelation* treatment and user's average voters' attractiveness levels. For the female cohort, as seen across Models 1 in Table 13A, the interaction term shows a positive and significant effect for self-initiated matches. Accordingly, a unit increase in average male voters' attractiveness for a female treated user will increase her matches sent by 6.82%. This result showcases an "encouragement effect," whereby increase in attractiveness of male voters, who provide 'like-votes' to treated female user, can encourage the treated female user to increase her self-initiated matching activities with potential mates. To look at females' engagement outcomes, in Table A15, the interaction term between treatment and user's average voters' attractiveness levels shows a significant increase in self-initiated views and messages. The treatment effect on outbound messages increases by 4.08% and outbound views increased by 17.47%. This suggests that the "encouragement effect" directly fills the gap in the earlier study Bapna et al. (2016), whereby our *strong signaling* intervention induces female users to visit and message others more often and ultimately, achieve more matches. For the male cohort, we didn't find evidence for an "encouragement effect" at the 95% level of significance.

Finally, we analyze the effects of the three-way interaction term that interacts the *vote-identity revelation* treatment with user's own attractiveness level and user's average voters' attractiveness level on the treated users matching outcomes (See even numbered models in Table 13A and 13B). For the female cohort, in Model 2 and 4, the three-way interaction term shows a negative and significant coefficient for both outbound and inbound matches, respectively. Further, in Table A15, the three-way interaction term reports negative and significant coefficients for views and messages both sent and received (Models 2, 4, 6 and 8). These results show an interesting phenomenon, where the joint increment of own attractiveness and average voters' attractiveness have a negative impact on the treated female users online dating outcomes. Accordingly, female users have less counts of profile browsing, messaging, and matching. We will have to look further to explain this unique result. One explanation is that all users invest more of their time in self-improvement by improving their profile pages and profile pictures due to exposure to the *vote-identity* revelation treatment. This will lead to increase in their attractiveness. As a result, they have less time to browse other profiles and message their potential mates, while engaged in self-improvement. Evidence in support of this explanation will require further study.

For the male cohort, we find a similar negative and significant effect for the 3-way interaction term for their self-initiated matches only (Model 2 of Table 13B). We further report the results from the attractiveness analysis related to male users' engagement outcomes, like viewing and messaging in Appendix Table A16.

Table 13A: Impact of Attractiveness for Females

	Match Sent		Match Received	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Treatment	0.277***	0.315***	0.221***	0.234***
	(0.04)	(0.04)	(0.02)	(0.02)
Treatment *				
Own Attractiveness	-0.022	0.020	0.015	0.029
	(0.05)	(0.05)	(0.02)	(0.02)
Average Voters' Attractiveness	0.066**	-0.055	0.016	-0.002
	(0.03)	(0.04)	(0.02)	(0.02)
Own Attractiveness * Average Voters' Attractiveness		-0.198***		-0.070***
		(0.04)		(0.02)
Controls	✓	✓	✓	✓
Observations	3305	3305	3305	3305

Note. Treatment is the *vote-identity revelation* binary indicator variable. Poisson regression model is used since dependent variables are count variables. Standard errors are reported in parentheses below coefficient values. All control variables reported in the paper are included. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 13B: Impact of Attractiveness for Males

	Match Sent		Match Received	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Treatment	0.163***	0.167***	0.076*	0.073*
	(0.02)	(0.02)	(0.04)	(0.04)
Treatment *				
Own Attractiveness	0.033**	0.043**	-0.014	-0.020
	(0.02)	(0.02)	(0.04)	(0.04)
Average Voters' Attractiveness	-0.030*	-0.023	0.043	0.036
	(0.02)	(0.02)	(0.04)	(0.04)
Own Attractiveness * Average Voters' Attractiveness		-0.037***		0.021
		(0.01)		(0.03)
Controls	✓	✓	✓	✓
Observations	7082	7082	7082	7082

Note. Treatment is the *vote-identity revelation* binary indicator variable. Poisson regression model is used since dependent variables are count variables. Standard errors are reported in parentheses below coefficient values. All control variables reported in the paper are included. * p < 0.10, ** p < 0.05, *** p < 0.01.

6. Discussion and Conclusion

The process of selecting a partner is often complicated by the information asymmetries between individuals and the known gender asymmetries in preferences and inhibitions. With the emergence and growth of online dating sites, we see these platforms implementing technology-enabled features that help reduce the information asymmetries. Interestingly, we find that these features can also help to mitigate social inhibitions that prevent women from initiating interactions with a potential mate.

In this paper, we employ a randomized field experiment to examine one of these technology-enabled features, what we call *vote-identity revelation*, in partnership with a large North American online dating site. The field experiment allows us to causally examine the relationship between treated users who can view the identity of the user(s) (or voter(s)) who voted them with a like-vote, and the control users who lack this ability on a variety of online dating outcomes, like viewing, messaging, and matching with another user. Prior work has demonstrated the importance of sending a 'weak-signal' through non-anonymous profile browsing for women in particular (Bapna et al. 2016). In this paper, we focus on the impact of a feature that allows users to receive a *strong-signal*. Further, we looked at heterogeneity in treatment effects along user's demographic dimensions, like age group, ethnicity and body type. Finally, we looked at whether users of different personal attractiveness levels or users with different average voters' attractiveness have a divergent reaction to *the vote-identity revelation* treatment.

Our results indicate increase in overall activity in the online dating site for both female and male cohorts, where more importantly, we found increase in self-initiated views and messages for female users, who were known not to initiate communication in online dating situations. When we look for the heterogeneity in treatment effects along users' demographic dimensions, we find that different demographic cohorts react differently to the treatment. A good example capturing this behavior is showcased by the Asian ethnic group. We find that under the effect of the treatment, Asian females show significant increase in their match related outcomes, yet Asian men had a significant decrease in their self-initiated matches. When looking at the results along the attractiveness dimension, we find that different genders react differently to the own attractiveness and average voters' attractiveness constructs. For instance, males show a positive "ego effect," whereby highly attractive males reduce their self-initiated online dating engagement activities (i.e. views and messages) yet achieve more out-bound matches. This is interesting given that it is common knowledge that in order to increase matches users should increase their engagement outcomes. Yet for highly attractive males our results show a decrease in engagement outcomes along with an increase in matches. For the females, we could see an "encouragement effect," when like-votes from highly attractive potential partners influence female users to increase their online dating activities. Given that a key challenge in dating markets is for women to initiate interaction with a potential partner, this finding is key to unlock the mechanism to overcome this gender specific inhibitions. In conclusion, our results show divergent effects due to the treatment along the attractiveness dimensions. Accordingly, the highly attractive male cohort of individuals react based on their "ego" due to the treatment by strategizing improvements in their matching outcomes, while selectively engaging with lesser number of potential partners; while the female cohort of users, react to a boosts in their confidence due to an "encouragement effect" due to like-votes from an attractive group of male users. Further, we find an interesting negative effect when treatment interacts with both users' own attractiveness and average voters' attractiveness. This result can suggest that users take part in self-improvement of their online dating profiles, and accordingly reduce dating website engagement and matching activities. This result suggests another set of online dating activities, where the access to identity-related information of other users makes focal users self-aware of their own identity. Accordingly, focal users invest effort in improving own identity by updating their profile picture and profile pages, which in turn increases their attractiveness. Finally, this leads to overall decrease in engagement and matching activity in the online dating site as users are busy updating their own identity.

Broadly speaking, the results of this study demonstrate that technology-enabled features can have an important impact on matching markets and therefore have implications for the design of such sites. Online dating sites face the unique challenge of wanting to maintain users while still providing them a successful service, i.e. finding them a match. While these two objectives are seemingly in conflict with one another, our discussions with monCherie.com management has indicated that the incentive to match people successfully is high as it creates offline word-of-mouth and generates a new set of users. Thus, implementing these technology-enabled features in such a way that can maximize the benefit of the users is important, and the results of this study can help online dating sites do that.

Conclusion

This dissertation aims to advance the existing literature on how online platforms and IT-enabled technologies impacts human societal and human relationships situations. By examining the role that the technology play towards solving societal challenges, like helping individuals find dates online, or in an unintended manner, how technology artifacts can exacerbate societal challenges, like prevalence of prostitution in online classified advertisement portals, we contribute with this dissertation to the interface between technology and human society and human relationships at large.

Looking with a macroscopic view at human societal challenges, in the first essay we study the unintentional consequence of Craigslist website's entry in United States' counties that can have an impact on prostitution incidences in the country. The essay further looks at the potential pathways by which Craigslist's entry can impact prostitution trends. For instance, was the prostitution market facilitated by Craigslist made up of independent sex workers, workers coerced under commercial vice groups, or both? To examine these questions empirically, we use data of Craigslist's entry from Craigslist's website and a novel data set on prostitution activities from *TheEroticReview.com* website. Further, using a difference-in-difference estimation approach on a panel data from 1999 to 2008, we study the impact of Craigslist on prostitution. The findings show that Craigslist's arrival in the market led not only to the overall increase in prostitution incidences in the United States significantly, but also increased both independent and coerced sex workers who are under the control of commercial vice groups. Further, we find Craigslist increased transactions for existing and increased entry of new sex workers during the study period. As a consequence, the first essay contributes to the unintended role that online platforms can play by allowing the operation of illegal markets, like that of prostitution. From a practical point of view, the essay identifies potential mechanisms that are operating behind the scenes in the online prostitution market. This can make policy makers, legal agencies, academicians, law enforcement and other stakeholders take policy relevant actions to tackle online prostitution.

In the second chapter of the thesis, we take a microscopic approach where we look at IT-enabled technology feature and its impact on online dating engagement and matching outcomes. Extant research has shown the importance of online dating towards matching singles with potential mates, and even leading to marriages (Cacioppo et al. 2013). These online dating websites provide a plethora of IT-enabled features to overcome frictions present in the real world. In order to investigate the importance of one very essential IT-enabled feature, in this essay we study the impact of *vote-identity revelation* feature on online dating users' engagement and matching outcomes. Particularly, given that different cohorts of users react differently under the influence of a treatment, we study heterogeneity in treatment effects along the following dimensions: gender, age group, ethnicity, and body type. Finally, we look along the attractiveness dimensions for treatment effects as it is ambiguous how attractive users will react to our interventions. To study these questions, we collaborate with a large North American online dating website and run randomized field experiment to implement *vote-identity revelation* feature. Our results find a significant increase in engagement and matching outcomes for both female and male users. We find that different cohorts of users react differently to the intervention. More interestingly, we find a positive "ego effect" for male users, and an "encouragement effect" for female users. The essay contributes to the existing literature in online dating and online ratings. It shows the importance of a specific IT-enabled feature that induces user behavior by providing a “strong signal.” Further, it not only looks for main treatment effects, but also identifies heterogeneity in treatment effects that has practical use for online dating website management in order to identify which user cohorts will be most benefited by this IT-enabled feature. This approach of identifying treatment effects helps stakeholders to make better website design decisions keeping in mind the innate differences among user cohorts.

There are a few limitations in the two essays that provide scope for future research to expand on these works. Firstly, it is possible that other sites or mobile apps can facilitate exchange for prostitution as well as the market for online dating. Regarding solicitation of sex workers, we considered an online classified advertisement website, whereas for the online dating market we partnered with a large online dating website. Other platforms that are not an online classified advertisement platform or a major dating website, can provide different sets of payoffs and costs which can lead to different outcomes in these markets. For instance, mobile apps like Tinder has been reported to be used by sex workers, whereas the IT-enabled features of such an app can create a very different user experience for legitimate online dating users (Dewey 2014). Secondly, geographically both our studies only look at markets in the United States, which leaves the scope to study online intermediaries and IT-enabled features relevant to the market for sex work and that for online dating in other geographies outside the United States. Finally, our studies restrict themselves to a specific timeline and economic lenses. For the first essay, we look at the market for sex work between years 1999 to 2008 using a macroscopic lens. Whereas, in the second essay we look at dating markets in the year

2016 spanning three months from a microscopic lens. Accordingly, our studies are restricted in providing a full picture, whereby we look at the problems using the entire scope of timeframe and economic lenses. This gives scope for future studies that can show the impact of online intermediaries and IT-enabled features on these markets spanning a larger spectrum of timelines and economic lenses.

Given the limitations, both essays try to systematically study the impact of online intermediaries and IT-enabled features on human societal outcomes, like prostitution, and romantic relationship outcomes, like dating. We make the first empirical study when looking at the impact of Craigslist's entry on prostitution incidences, whereas it is the first systematic study of the impact of a specific IT-enabled feature, i.e. *vote-identity revelation* feature. As the prevalence of online intermediaries and website features become ubiquitous connecting all types of human activities, the study of their impact on societal and relational outcomes become important. On one hand, their unintended use can create markets for illegal activities to flourish, yet on the other hand, proper use of technology artifacts can impact human society in a positive manner, like improving the timeless social process of finding a date.

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Appendix 1 - Tables

Table A1: Number of Counties Per State in the Data Set

State	No. of Counties in Data	Total No. of Counties	State	No. of Counties in Data	Total No. of Counties
Alabama	38	67	Montana	0	56
Alaska	25	30	Nebraska	85	93
Arizona	4	15	Nevada	10	17
Arkansas	50	75	New Hampshire	9	10
California	15	58	New Jersey	5	21
Colorado	55	64	New Mexico	20	33
Connecticut	4	8	New York	12	62
Delaware	3	3	North Carolina	36	100
Florida	65	67	North Dakota	0	53
Georgia	71	159	Ohio	22	88
Hawaii	2	5	Oklahoma	61	77
Idaho	40	44	Oregon	24	36
Illinois	95	102	Pennsylvania	20	67
Indiana	25	92	Rhode Island	4	5
Iowa	84	99	South Carolina	19	46
Kansas	95	105	South Dakota	0	66
Kentucky	52	120	Tennessee	57	95
Louisiana	10	64	Texas	173	254
Maine	13	16	Utah	25	29
Maryland	3	24	Vermont	9	14
Massachusetts	11	14	Virginia	91	133
Michigan	61	83	Washington	16	39
Minnesota	63	87	West Virginia	47	55
Mississippi	44	82	Wisconsin	39	72
Missouri	84	115	Wyoming	0	23
Total No. of Counties in Data					1796

Table A2: Robustness Checks

Prostitution Definition	Main Model Model 1	Un-weighted Regression Model 2	Population-Normalized DV Model 3	Prostitution Only Counties Model 4	With Time-Varying county-specific Controls Model 5	Alt. Dependent Variable Model 6
TER: All Years (Using	0.199*** (0.03)	0.170*** (0.02)	0.200*** (0.03)	0.200** (0.08)	0.47** (0.02)	
TER: Active Years	0.162*** (0.03)	0.137*** (0.02)	0.163*** (0.03)	0.139* (0.07)	0.033* (0.02)	
TER Reviews (Using						0.260*** (0.04)

Note. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All reported coefficients in the table are for the Craigslist Entry regressor. All control variables reported in Table 2 are included. In Model 5 additional time-varying county-specific controls are used. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Covariate Balance Check for One-to-One Without Replacement Propensity Score Matching

Variables	Unmatched (U) / Matched (M)	Mean		Bias (%)	Bias Reduction (%)	t-test	
		Treated	Control			t-value	p-value
Age 15-19 Proportion	U	0.076	0.075	5.2		1.05	0.295
	M	0.075	0.074	4.1	20.7	0.52	0.601
Age 20-39 Proportion	U	0.264	0.236	62.8		12.32	0.000
	M	0.252	0.252	0.1	99.9	0.01	0.992
Age 40-59 Proportion	U	0.278	0.274	15		3	0.003
	M	0.28	0.282	-6.9	53.6	-0.82	0.413
White Proportion	U	0.887	0.901	-9.5		-1.69	0.091
	M	0.9	0.905	-3.4	64.3	-0.45	0.653
African American Proportion	U	0.082	0.077	3.8		0.68	0.499
	M	0.074	0.073	1.1	71.1	0.15	0.885
Asian Proportion	U	0.013	0.004	43.2		10.21	0.000
	M	0.008	0.007	4.6	89.4	0.86	0.393
Population Size	U	120000	25474	54.8		13.02	0.000
	M	55776	46400	5.3	90.3	1.04	0.299
Poverty	U	14068	2975.8	50.4		12.55	0.000
	M	5934.6	4946.5	4.5	91.1	1.32	0.187
Employed Proportion	U	0.944	0.947	-16.4		-2.92	0.003
	M	0.942	0.941	10.1	38.0	1.14	0.255
Annual Mean Income	U	38184	33880	52.2		10	0.000
	M	36534	36607	-0.9	98.3	-0.11	0.916
Broadband Penetration	U	2.957	2.368	61.5		13.36	0.000
	M	2.578	2.56	2	96.8	0.29	0.773
Police Officers	U	218.05	47.068	44.2		10.68	0.000
	M	93.013	74.606	4.8	89.2	1.1	0.270
Offense Against Family and Children	U	46.677	8.709	41.1		10.05	0.000
	M	19.344	17.3	2.2	94.6	0.47	0.638
Runaway Individuals	U	40.302	6.836	35.1		8.14	0.000
	M	18.592	16.754	1.9	94.5	0.3	0.764
Drug Related Crimes	U	424.41	66.419	50.4		12.61	0.000
	M	138.17	130.58	1.1	97.9	0.35	0.728

Table A4: Covariates Predicting Craigslist entry

Variables	Coefficient (SE)
Age 15-19 Proportion	17.574***
	(6.71)
Age 20-39 Proportion	11.908***
	(2.10)
Age 40-59 Proportion	22.657***
	(3.72)
White Proportion	3.400**
	(1.45)
African American Proportion	2.273
	(1.50)
Asian Proportion	17.304*
	(9.69)
Population Size	-0.000***
	(0.00)
Poverty	0.000***
	(0.00)
Employed Proportion	-23.489***
	(4.11)
Annual Mean Income	0.000***
	(0.00)
Broadband Penetration	-0.099
	(0.16)
Police Officers	-0.002**
	(0.00)
Offense Against Family and Children	0.003
	(0.00)
Runaway Individuals	-0.002
	(0.00)
Drug Related Crimes	0.003***
	(0.00)
Pseudo R^2	0.2678
Observations	1757

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness Checks with Matching Estimates

Prostitution Definition	Main Model	Propensity Score Matching (Nearest Neighbor Matching)				
		NN=1 (w/o)	NN=1 (w)	NN=2 (w)	NN=3 (w)	NN=4 (w)
	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5
TER: All Years	0.199***	0.069***	0.078***	0.059***	0.053**	0.049**
(Using Craigslist)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
TER: Active Years	0.162***	0.050**	0.057***	0.038**	0.032*	0.029
(Using Craigslist)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	16735	15492	15966	15598	15448	15357
		Propensity Score Matching (Kernel Matching)				
		BW=0.06	BW=0.03	BW=0.015	BW=0.001	BW=0.0001
		Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5
TER: All Years		0.086***	0.086***	0.089***	0.055**	0.073**
(Using Craigslist)		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
TER: Active Years		0.064***	0.064***	0.066***	0.043**	0.051*
(Using Craigslist)		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Observations		16119	16119	16040	9748	2141
		Coarsened Exact Matching (CEM)				
		Cut off 2	Cut off 3	Cut off 4	Cut off 5	Cut off 6
		Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5
TER: All Years		0.197***	0.142***	0.120***	0.086***	0.051***
(Using Craigslist)		(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
TER: Active Years		0.161***	0.110***	0.090***	0.064***	0.032**
(Using Craigslist)		(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Observations		16660	16304	15401	14308	12134

Note. Model 1.0 is same as Model 5 (DV= TER: All Years - Using Craigslist) and Model 7 (DV= TER: Active Years - Using Craigslist) from Table 2. NN=k implies k-nearest neighbors, where (w/o) is without replacement, and (w) is with replacement. In kernel matching, we used Epanechnikov kernel for different values of bandwidth (BW) as mentioned in Model 2.1 to Model 2.5. Equally spaced cut-off points of values 2 to 6 were used on the co-variates to perform Coarsened Exact Matching (CEM). All control variables reported in Table 2 are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Relationship between Entry Patterns and Existing Prostitution Trends

	DV = Craigslist Entry		
Variables	**Model 1**	**Model 2**	**Model 3**
TER: All Years (Using Craigslist)	0.026 (0.06)		
TER: Active Years (Using Craigslist)		0.027 (0.06)	
Log (Commercial Vice Crimes)			0.050 (0.04)
R-squared	0.837	0.837	0.837
F-Stats	5575.22	5575.10	5709.09
Observations	2049	2049	2049

Note. The dependent variable for Models 1 to 3 is the binary website entry variable 'Craigslist Entry'. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All control variables reported in Table 2 are included. All models are weighted regressions with county and year fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A7: Falsification Test Using Alternative Crimes

	Larceny	**Arson**	**Burglary**
Variables	**Model 1**	**Model 2**	**Model 3**
Craigslist Entry	-0.034 (0.02)	0.020 (0.02)	-0.019 (0.02)
R-squared	0.328	0.027	0.216
F-Stats	57.949	11.033	56.543
Observations	16735	16735	16735

Note. The dependent variables for Model 1 to 3 are the log number of larceny, arson and burglary, respectively. Robust standard errors clustered by counties are reported in parentheses below coefficient values. All control variables and fixed effects reported in Table 2 are included. * p < 0.10, ** p < 0.05, *** p < 0.01

Table A8: t-test Results for Main Treatment Effects

Gender	Measure	Mean (C)	Mean (T)	Percent Difference	t-value	p-value
Both Gender	Total Matches	1.043	1.175	12.587	-3.895	0.000
Female	Total Matches	1.265	1.489	17.685	-3.659	0.000
Male	Total Matches	0.918	0.994	8.270	-1.910	0.056
Female	Matches Sent	0.203	0.243	19.717	-2.421	0.015
Female	Matches Received	1.063	1.246	17.298	-3.532	0.000
Female	Messages Sent	2.373	2.667	12.403	-2.632	0.008
Female	Msg Received	9.051	9.684	6.994	-1.894	0.058
Female	Views Sent	10.925	12.740	16.615	-2.994	0.003
Female	Views Received	35.913	37.935	5.632	-1.820	0.069
Male	Matches Sent	0.797	0.860	7.783	-1.667	0.095
Male	Matches Received	0.121	0.135	11.482	-2.322	0.020
Male	Messages Sent	7.636	7.737	1.322	-0.301	0.763
Male	Msg Received	1.904	1.993	4.671	-1.321	0.187
Male	Views Sent	28.033	28.577	1.944	-0.600	0.549
Male	Views Received	7.483	7.681	2.654	-0.899	0.369

Note. Mean (C) and Mean (T) represents sample means for control group and treatment group, respectively. In the data, there are 38,478 females, and 61,522 males, giving the total of 100,000 users. Highlighted rows show cases with p-value < 0.01. Msg is messages.

Table A9: t-test Results for Heterogeneous Treatment Effects for Age Groups

Gender	Age Groups	Measure	Mean (C)	Mean (T)	Percent Difference	t-value	p-value
Female	18 to 24	Matches Sent	0.388	0.465	19.840	-0.664	0.507
Female	18 to 24	Matches Received	2.284	3.554	55.622	-2.419	0.016
Female	25 to 29	Matches Sent	0.584	0.696	19.153	-0.656	0.512
Female	25 to 25	Matches Received	2.505	3.057	22.029	-1.255	0.210
Female	30 to 39	Matches Sent	0.502	0.628	25.175	-1.135	0.257
Female	30 to 39	Matches Received	2.620	2.608	-0.469	0.034	0.973
Female	40 to 49	Matches Sent	0.634	1.095	72.691	-2.403	0.017
Female	40 to 49	Matches Received	3.900	4.117	5.571	-0.353	0.724
Female	50+	Matches Sent	0.882	0.918	4.162	-0.127	0.899
Female	50+	Matches Received	2.746	3.899	42.010	-1.779	0.076
Male	18 to 24	Matches Sent	0.962	1.073	11.559	-0.711	0.477
Male	18 to 24	Matches Received	0.163	0.172	5.254	-0.364	0.716
Male	25 to 29	Matches Sent	1.837	2.052	11.709	-0.651	0.515
Male	25 to 25	Matches Received	0.284	0.295	3.626	-0.234	0.815
Male	30 to 39	Matches Sent	1.949	2.263	16.107	-1.086	0.277
Male	30 to 39	Matches Received	0.372	0.443	19.010	-1.386	0.166
Male	40 to 49	Matches Sent	1.754	2.642	50.646	-1.733	0.084
Male	40 to 49	Matches Received	0.481	0.452	-6.126	0.368	0.713
Male	50+	Matches Sent	1.831	1.577	-13.886	0.567	0.571
Male	50+	Matches Received	0.451	0.433	-4.048	0.180	0.857

Note. Mean(C) and Mean(T) represents sample means for control group and treatment group, respectively.

Table A10: t-test Results for Heterogeneous Treatment Effects for Ethnicity

Gender	Ethnicity	Measure	Mean (C)	Mean (T)	Percent Difference	t-value	p-value
Female	White	Matches Sent	0.594	0.662	11.506	-0.812	0.417
Female	White	Matches Received	2.898	3.125	7.821	-0.863	0.388
Female	Black	Matches Sent	0.555	0.667	20.106	-0.632	0.528
Female	Black	Matches Received	2.692	3.391	25.981	-1.100	0.272
Female	Asian	Matches Sent	0.350	0.913	161.351	-2.644	0.009
Female	Asian	Matches Received	2.189	4.260	94.563	-2.416	0.016
Female	Mixed Race	Matches Sent	0.474	0.901	89.979	-1.276	0.204
Female	Mixed Race	Matches Received	1.828	4.160	127.639	-2.643	0.009
Male	White	Matches Sent	1.622	1.847	13.833	-1.388	0.165
Male	White	Matches Received	0.327	0.341	4.284	-0.533	0.594
Male	Black	Matches Sent	1.310	1.970	50.417	-1.987	0.047
Male	Black	Matches Received	0.284	0.297	4.734	-0.216	0.829
Male	Asian	Matches Sent	1.429	0.725	-49.291	1.957	0.051
Male	Asian	Matches Received	0.175	0.136	-22.323	0.878	0.380
Male	Mixed Race	Matches Sent	1.646	2.390	45.153	-1.256	0.210
Male	Mixed Race	Matches Received	0.303	0.365	20.569	-0.587	0.558

Note. Mean(C) and Mean(T) represents sample means for control group and treatment group, respectively. Highlighted rows show cases with p-value < 0.01.

Table A11: t-test Results for Heterogeneous Treatment Effects for Body Types

Gender	Ethnicity	Measure	Mean (C)	Mean (T)	Percent Difference	t-value	p-value
Female	Average	Matches Sent	0.587	0.647	10.291	-0.479	0.632
Female	Average	Matches Received	2.227	2.409	8.208	-0.711	0.477
Female	Fit	Matches Sent	0.540	0.526	52.955	-1.847	0.065
Female	Fit	Matches Received	3.270	3.677	12.436	-0.676	0.499
Female	Curvy	Matches Sent	0.536	0.679	26.755	-1.280	0.201
Female	Curvy	Matches Received	2.991	4.275	42.907	-2.570	0.010
Female	Full Figured	Matches Sent	0.514	0.761	48.191	-1.268	0.206
Female	Full Figured	Matches Received	3.050	3.376	10.687	-0.519	0.604
Male	Average	Matches Sent	1.376	1.454	5.622	-0.499	0.618
Male	Average	Matches Received	0.274	0.287	4.902	-0.510	0.610
Male	Fit	Matches Sent	1.875	2.279	21.566	-1.667	0.096
Male	Fit	Matches Received	0.360	0.369	2.635	-0.244	0.807
Male	Curvy	Matches Sent	0.583	0.946	62.162	-0.975	0.333
Male	Curvy	Matches Received	0.083	0.108	29.730	-0.278	0.782
Male	Full Figured	Matches Sent	0.207	1.189	474.775	-1.713	0.095
Male	Full Figured	Matches Received	0.069	0.270	291.892	-1.817	0.075

Note. Mean(C) and Mean(T) represents sample means for control group and treatment group, respectively. Highlighted rows show cases with p-value < 0.01

Table A12: Engagement Outcomes for Curvy Females

Gender	Measure	Mean (C)	Mean (T)	Percent Difference	t-value	p-value
Female	Views Sent	24.2	36.7	51.5	-2.9	0.004
Female	Messages Sent	6.3	8.3	33.4	-2.3	0.019

Note. Mean (C) and Mean (T) represents sample means for control group and treatment group, respectively. Highlighted rows show cases with p-value < 0.01.

Table A13: Detailed Heterogeneous Treatment Effects Along Demographic Dimensions For Females

	Views		Messages		Matches	
	Sent	Rcvd	Sent	Rcvd	Sent	Rcvd
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment	0.115***	0.051***	0.157***	0.103***	0.223***	0.173***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.04)	(0.02)
Age groups -						
18 to 24 ages	-0.519***	0.119***	-0.531***	-0.057***	-0.783***	-0.237***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
25 to 29 ages	-0.106***	0.381***	-0.400***	0.061***	-0.374***	-0.253***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
30 to 39 ages	-0.088***	0.244***	-0.415***	-0.113***	-0.487***	-0.282***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
40 to 49 ages	0.106***	0.336***	-0.052**	0.110***	-0.085	0.144***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
Ethnicities -						
Asian	-0.085***	-0.208***	0.073***	-0.108***	-0.013	0.101***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
Black	-0.025***	-0.357***	0.037*	-0.398***	0.028	0.031
	(0.01)	(0.01)	(0.02)	(0.01)	(0.06)	(0.03)
Mixed Race	-0.014	-0.008	0.020	-0.074***	0.155*	-0.091**
	(0.01)	(0.01)	(0.03)	(0.01)	(0.09)	(0.04)
Body types -						
Average	-0.028**	0.133***	-0.170***	0.150***	-0.027	-0.337***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.07)	(0.03)
Curvy	0.092***	0.336***	0.109***	0.385***	0.022	0.132***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.08)	(0.03)
Fit	0.367***	0.458***	0.129***	0.466***	0.070	0.054
	(0.01)	(0.01)	(0.02)	(0.01)	(0.08)	(0.04)
Treatment interactions with						
Age groups -						
18 to 24 ages	-0.272***	-0.101***	-0.069	-0.045*	-0.022	-0.104
	(0.02)	(0.01)	(0.04)	(0.02)	(0.14)	(0.07)
25 to 29 ages	-0.106***	0.064***	-0.068	0.099***	-0.012	-0.285***
	(0.02)	(0.01)	(0.04)	(0.03)	(0.14)	(0.07)
30 to 39 ages	0.023	-0.058***	-0.195***	-0.030	0.069	-0.459***
	(0.02)	(0.01)	(0.04)	(0.02)	(0.13)	(0.07)
40 to 49 ages	-0.234***	-0.155***	-0.098**	-0.026	0.428***	-0.374***
	(0.02)	(0.01)	(0.04)	(0.03)	(0.14)	(0.07)
Ethnicities -						
Asian	0.464***	0.418***	0.597***	0.557***	0.855***	0.609***
	(0.02)	(0.01)	(0.04)	(0.02)	(0.15)	(0.06)
Black	-0.205***	-0.073***	0.054	-0.004	0.041	0.134**
	(0.02)	(0.01)	(0.04)	(0.02)	(0.13)	(0.06)
Mixed Race	0.669***	0.459***	0.548***	0.506***	0.528***	0.696***
	(0.03)	(0.01)	(0.05)	(0.03)	(0.17)	(0.08)
Body types -						
Average	-0.475***	-0.006	-0.300***	0.046*	-0.390***	-0.069
	(0.02)	(0.01)	(0.05)	(0.03)	(0.15)	(0.07)
Curvy	0.104***	0.076***	0.029	0.013	-0.204	0.208***
	(0.02)	(0.01)	(0.05)	(0.03)	(0.15)	(0.07)
Fit	-0.310***	0.076***	0.001	0.135***	-0.066	-0.024
	(0.02)	(0.01)	(0.05)	(0.03)	(0.16)	(0.07)
Observations	3858	3858	3858	3858	3858	3858

Note. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A14: Detailed Heterogeneous Treatment Effects Along Demographic Dimensions For Males

	Views		Messages		Matches	
	Sent	**Rcvd**	**Sent**	**Rcvd**	**Sent**	**Rcvd**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Treatment	0.052***	0.012**	0.085***	0.057***	0.103***	0.048
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
Age groups -						
18 to 24 ages	-0.503***	-0.888***	-0.527***	-0.816***	-0.543***	-0.965***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)
25 to 29 ages	0.079***	-0.141***	0.004	-0.203***	0.092***	-0.426***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)
30 to 39 ages	0.276***	0.174***	0.173***	-0.002	0.183***	-0.083
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)
40 to 49 ages	0.359***	0.198***	0.186***	0.077***	0.190***	0.030
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)
Ethnicities -						
Asian	-0.221***	-0.538***	-0.241***	-0.533***	-0.489***	-0.653***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.10)
Black	0.014***	-0.222***	0.157***	-0.152***	-0.095***	-0.121*
	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)
Mixed Race	0.213***	0.170***	0.281***	0.124***	0.169***	0.080
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)
Body types -						
Average	0.612***	0.563***	1.127***	0.695***	0.984***	0.615
	(0.03)	(0.05)	(0.08)	(0.11)	(0.22)	(0.39)
Curvy	0.507***	0.158**	0.171*	-0.071	0.365	-0.397
	(0.03)	(0.06)	(0.10)	(0.14)	(0.26)	(0.55)
Fit	0.736***	0.895***	1.373***	1.049***	1.364***	0.916**
	(0.03)	(0.05)	(0.08)	(0.11)	(0.22)	(0.39)
Treatment interactions with						
Age groups -						
18 to 24 ages	0.013	0.051**	0.148***	0.164***	0.250***	0.103
	(0.01)	(0.02)	(0.02)	(0.04)	(0.07)	(0.14)
25 to 29 ages	0.231***	0.107***	0.193***	0.185***	0.247***	0.084
	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.14)
30 to 39 ages	0.068***	0.097***	0.182***	0.227***	0.298***	0.238*
	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.13)
40 to 49 ages	0.139***	0.093***	0.274***	0.283***	0.512***	-0.034
	(0.01)	(0.02)	(0.02)	(0.04)	(0.07)	(0.14)
Ethnicities -						
Asian	-0.051***	-0.245***	-0.640***	-0.472***	-0.800***	-0.330*
	(0.01)	(0.02)	(0.02)	(0.05)	(0.08)	(0.19)
Black	0.181***	0.133***	0.172***	0.123***	0.244***	-0.032
	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.13)
Mixed Race	0.137***	0.014	0.050**	0.085**	0.193***	0.093
	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.15)
Body types -						
Average	-0.869***	-0.678***	-1.812***	-1.184***	-1.657***	-1.262
	(0.05)	(0.09)	(0.16)	(0.22)	(0.44)	(0.78)
Curvy	0.965***	-0.051	-1.183***	-0.869***	-1.210**	-1.031
	(0.07)	(0.12)	(0.20)	(0.29)	(0.52)	(1.09)
Fit	-0.796***	-0.614***	-1.695***	-1.085***	-1.537***	-1.293*
	(0.05)	(0.09)	(0.16)	(0.22)	(0.44)	(0.78)
Observations	8675	8675	8675	8675	8675	8675

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Detailed Impact of Attractiveness For Females

	Views				Messages				Matches			
	Sent		Received		Sent		Received		Sent		Received	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Treatment	0.153***	0.179***	0.062***	0.073***	0.211***	0.230***	0.103***	0.114***	0.277***	0.315***	0.221***	0.234***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)
Own Attractiveness	-0.146***	-0.141***	0.203***	0.203***	-0.066***	-0.066***	0.282***	0.282***	-0.336***	-0.339***	0.058***	0.058***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.03)	(0.03)	(0.01)	(0.01)
Average Voters' Attractiveness	-0.063***	-0.083***	-0.005***	-0.007***	0.051***	0.046***	0.021***	0.021***	0.087***	0.074***	0.047***	0.045***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)
Treatment *												
Own Attractiveness	-0.128***	-0.125***	0.032***	0.039***	0.008	0.026*	0.073***	0.083***	-0.022	0.020	0.015	0.029
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.02)	(0.02)
Average Voters' Attractiveness	0.161***	0.122***	0.010***	0.015***	0.040***	0.003	-0.011	-0.007	0.066**	-0.055	0.016	-0.002
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)
Own Attractiveness * Average Voters' Attractiveness		-0.160***		-0.061***		-0.101***		-0.061***		-0.198***		-0.070***
		(0.01)		(0.00)		(0.01)		(0.01)		(0.04)		(0.02)
Controls												
Age groups dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ethnicity dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Body type dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Intercept	3.504***	3.501***	4.619***	4.618***	1.992***	1.991***	3.204***	3.204***	-0.432***	-0.436***	1.183***	1.183***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	3305	3305	3305	3305	3305	3305	3305	3305	3305	3305	3305	3305

Note. Treatment is the *vote-identity revelation* binary indicator variable. Poisson regression model is used since dependent variables are count variables. Standard errors are reported in parentheses below coefficient values. All control variables reported in the paper are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Detailed Impact of Attractiveness For Males

	Views				Messages				Matches			
	Sent		Received		Sent		Received		Sent		Received	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Treatment	0.085***	0.087***	0.038***	0.039***	0.127***	0.138***	0.095***	0.097***	0.163***	0.167***	0.076*	0.073*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)
Own Attractiveness	-0.093***	-0.094***	0.032***	0.031***	-0.112***	-0.122***	0.117***	0.115***	0.051***	0.048***	0.145***	0.146***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Average Voters' Attractiveness	0.024***	0.024***	-0.001	-0.001	0.098***	0.095***	0.001	0.001	0.016*	0.017*	-0.032	-0.032
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Treatment *												
Own Attractiveness	-0.083***	-0.080***	-0.000	0.001	-0.051***	-0.018***	0.014	0.018*	0.033**	0.043**	-0.014	-0.020
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)
Average Voters' Attractiveness	-0.034***	-0.034***	-0.011**	-0.010*	-0.052***	-0.051***	-0.025**	-0.021*	-0.030*	-0.023	0.043	0.036
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)
Own Attractiveness * Average Voters' Attractiveness		-0.014***		-0.004		-0.095***		-0.013*		-0.037***		0.021
		(0.00)		(0.00)		(0.01)		(0.01)		(0.01)		(0.03)
Controls												
Age groups dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ethnicity dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Body type dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Intercept	4.114***	4.114***	2.858***	2.858***	2.728***	2.726***	1.479***	1.479***	0.581***	0.581***	-1.151***	-1.151***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	7082	7082	7082	7082	7082	7082	7082	7082	7082	7082	7082	7082

Note. Treatment is the *vote-identity revelation* binary indicator variable. Poisson regression model is used since dependent variables are count variables. 'Msg Rcvd' stands for messages received. Standard errors are reported in parentheses below coefficient values. All control variables reported in the paper are included. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix 2 - Figures

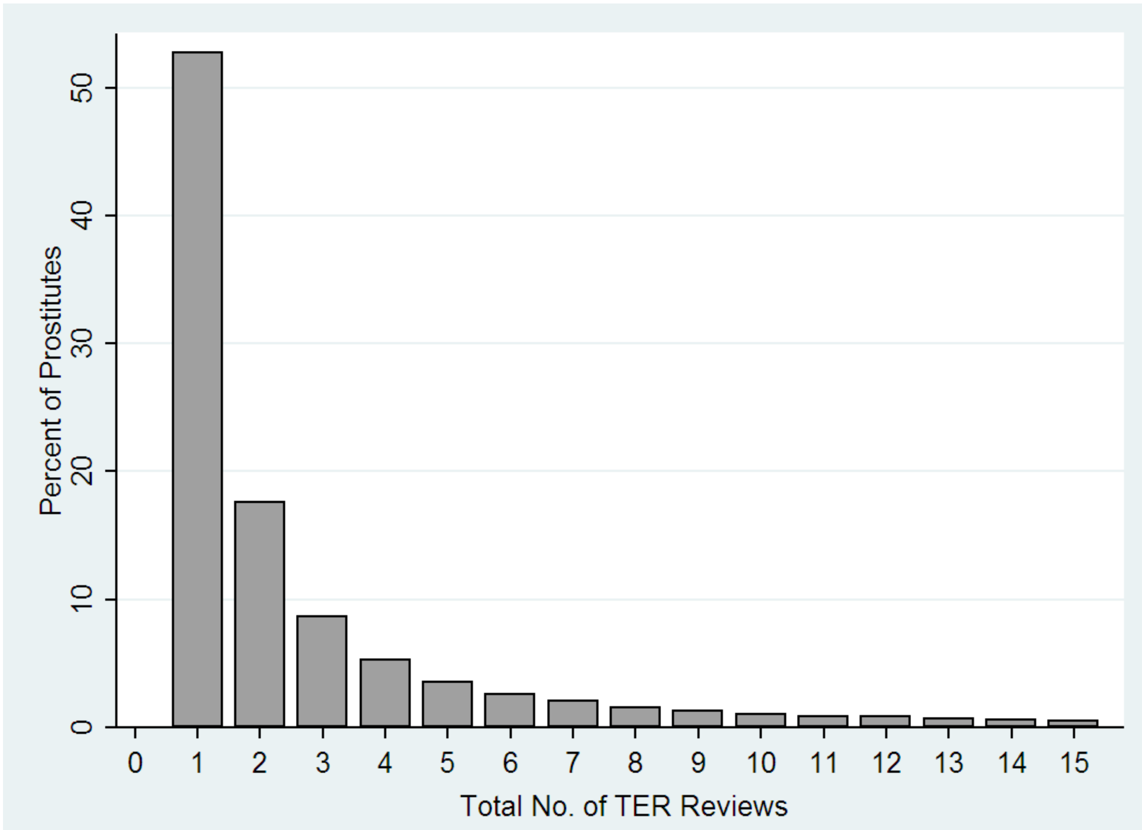

Figure A1: Distribution of prostitutes under different review count

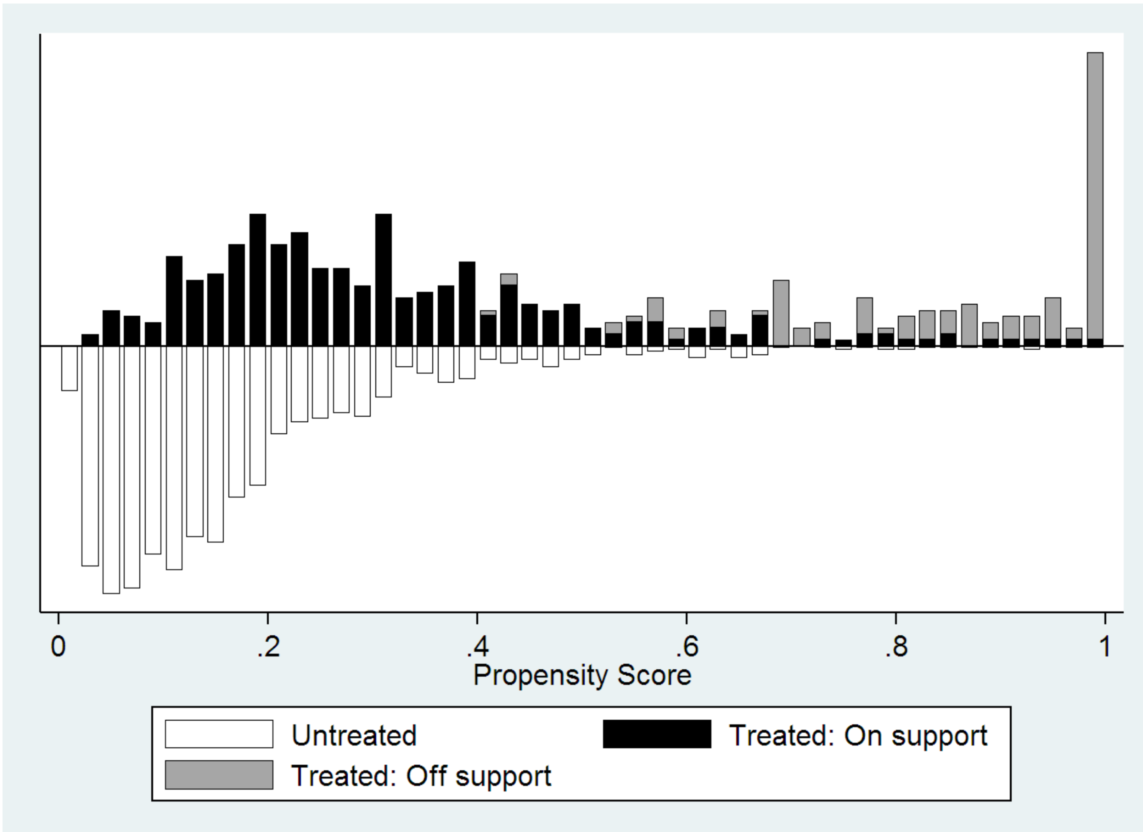

Figure A2: Propensity score distribution for the treated and control groups

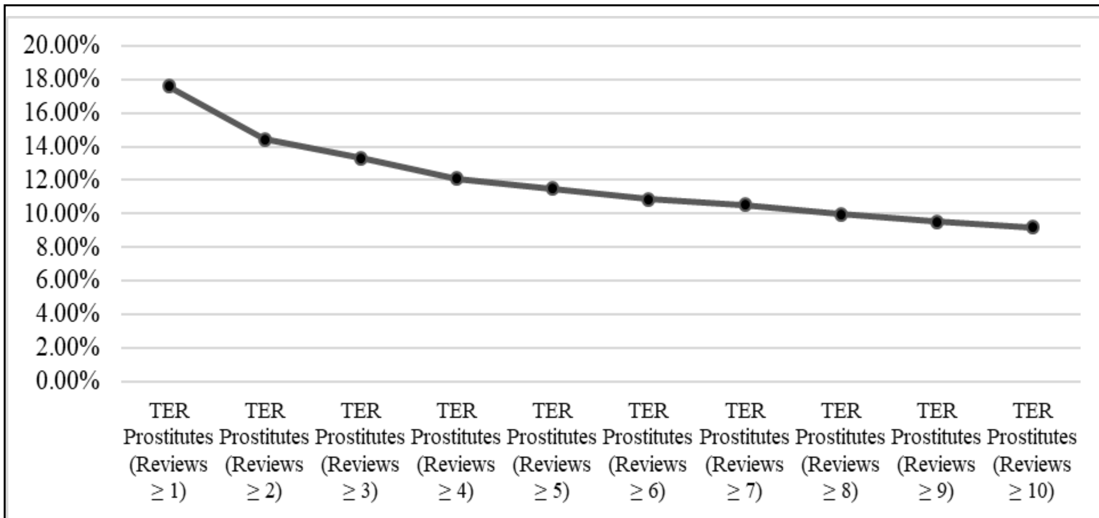

Figure A3 - Comparison of Effect Sizes

Note: This plot reports effect sizes (in the y-axis) on prostitution incidences due to Craigslist entry. Prostitution count under the definition of TER: Active Years (Using Craigslist) is the dependent variable used to plot the graph. All estimates reported in the figure are statistically significant at 5% level of α. X-axis reports different cases of the dependent variable based on prostitutes' review counts. TER Prostitutes (Reviews ≥ 1) is the dependent variable used in Model 7 of Table

Appendix 3 - Neighboring County Distance Measure

To check for the spillover effect mechanism, we used a sub-sample of pairs of neighboring counties where exactly one county has Craigslist entry and the other do not have Craigslist entry. In identifying each county-pair identified, we calculate the distance between these counties using the haversine formula, which accounts for the spherical nature of Earth's surface when calculating the shortest distance between two coordinates. In our case, each of these points is the latitude and longitude associated with each county, and the formula is as follows:

$$hav\left(\frac{shortest\ distance}{radius}\right) = hav(lat_2 - lat_1) + \cos(lat_1)\cos(lat_2)\,hav(long_2 - long_1)$$

where,

- $hav(\theta) = sin^2\left(\frac{\theta}{2}\right)$
- lat_1, lat_2: latitude of county 1 and latitude of county 2
- $long_1, long_2$: longitude of county 1 and longitude of county 2
- Radius = 3,959 miles (i.e. Earth's radius)

County-pairs that have the shortest distance are identified as neighboring counties and are used in our analysis. In our analysis, we restrict the length of our panel to the time period that only includes the first year of Craigslist entry to avoid the possibility of Craigslist entering in the neighboring county in subsequent years. To avoid the possibility of neighboring counties with Craigslist in an earlier period having an impact on the focal county that experienced site entry at a later period, we identified and removed county-pairs in which the second closest neighboring county to the focal county had experienced Craigslist entry in an earlier year. Through this procedure, we identified 126 county-pairs that fulfilled these criteria.